TRAINING EFFECTIVENESS OF PERSONALISED LEARNING ADOPTING EMERGING TECHNOLOGIES, IN DEFENCE SMALL AND MEDIUM ENTERPRISES AT HYDERABAD

Synopsis of the PhD Thesis

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TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
	Abstract	i
1.	**Introduction** 1.1 Overview 1.2 Problem Statement 1.3 Research Questions and Research Objectives	1-4
2.	**Literature Review and Theoretical Background** 2.1 Overview 2.2. Technology Enabled Learning (TEL) 2.3 Theoretical Frameworks for Technology Adoption in Personalised Learning 2.4 Research Gaps 2.5 Conceptualisation and Operationalisation of Constructs 2.6 Hypotheses Development	5-16
3.	**Research Methodology** 3.1 Research Design and Methodological Approach 3.2 Sample Design 3.3 Data Collection Procedure 3.4 Validity and Reliability 3.5 Pilot Study 3.6 Analysis of Pilot Study	17-21
4.	**Data Analysis and Findings** 4.1 Overview 4.2 Demographic Data Analysis 4.3 Normality of Data 4.4 Statistical Tools for Data Analysis 4.5 Data Analysis-Descriptive Statistics and Measurement Model 4.6 Structural Model Evaluation and Hypothesis Testing Results 4.7 Hypothesis Testing Table (Unstandardised Path Estimates) 4.8 Comprehensive Structural Model	22-30
5.	**Discussions and Conclusions** 5.1 Overview 5.2 Discussion of Key Finding 5.3 Contributions 5.4 Limitations of the Study 5.5 Future Scope of Research	31-39
	Research Publications- Journal and Conference Publications	40
	References	41-49

Abstract

With the rapid development of defence technologies through Make in India, there is a growing need for Indian Defence Small and Medium Enterprises (SMEs) to reskill and upskill their workforce. However, most traditional learning models do not focus on SME Employees' various learning styles and preferences, which in turn leads to a lack of engagement and limited learning effectiveness. This study explores the effectiveness of a personalised learning framework customised to individual learner preferences and the VARK model (Visual, Aural, Read/Write, Kinesthetics) with content delivery through the Canvas Learning Management System.

The study was based on the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating constructs such as Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, and Behavioural Intention, along with the Reaction level from Kirkpatrick's evaluation model. The study used a structured, multi-phase approach to develop and validate the framework and applied to a sample of 400 employees working in Defence SMEs of Hyderabad, with the help of Structural Equation Modelling (SEM) in IBM SPSS AMOS. The findings reveal that Effort Expectancy and Facilitating Conditions are strong predictors of Behavioural Intention to use personalised learning, the latter a strong predictor of learners' Reactions. Mediation analysis supported behavioural intention as a significant mediator between EE and FC on learner satisfaction. But the demographic factors and VARK modalities were not perceived as having a moderating influence on the adoption constructs.

This study contributes to the theory of UTAUT by extending the model through integration of Kirkpatrick's Reaction construct and VARK learning styles, offering a holistic model for personalised learning adoption in Defence SMEs. It contradicts the primacy of Performance Expectancy and Social Influence in formal defence settings. For practitioners, it offers practical strategies for deploying scalable and adaptive training systems aligned with organisational realities. Limitations include the geographic focus on Hyderabad SMEs, the exclusion of Social Influence from the final model, and the absence of real-time learning analytics. Future research should explore broader defence sectors, adopt longitudinal designs, and incorporate usage data to deepen understanding of long-term learning effectiveness.

Keywords: Personalised Learning, Defence SMEs, Training Effectiveness, Reaction and Behavioural Intention

Chapter 1

Introduction

1.1 Overview

Since the beginning of the "Make in India" initiative, defence production has experienced considerable growth, achieving a record ₹1.27 lakh crore in the fiscal year 2023-24. In addition, defence exports have increased to an unprecedented ₹23,622 crore in the fiscal year 2024-25. India's dependence on imported military technology from friendly countries has now been supplemented by indigenously developed resources and equipment, adding a new dimension to Indian military effectiveness. This indicated a clear drive on self-reliance towards manufacturing or providing services through domestic firms, ensuring that India fulfils its security requirements and adopting and motivating a strong defence industry to aid overall growth (Ministry of Defence, 2025).

1.1.1 *Role of SMEs in Atma Nirbhar Bharat*

At the heart of this Make in India transformation is Small Medium Enterprises(SMEs), which have emerged as a vital cog in the value chain, sourcing essential electronic systems, components, composite materials and precision assemblies for PSUs like HAL and BEL, and private defence private firms such as L&T Defence and Tata Advanced Systems (Wankhede, 2024). This change was visible in Operation SINDOOR (2025), India's controlled and high-technology military response to asymmetric warfare. The swift operation exhibited the successful and well-coordinated employment of indigenous platforms in electronic warfare, counter-drone systems, network-centric operations, and cyber-enabled surveillance—underscoring India's indigenous prowess to integrate home-grown systems on short notice to prepare for any external threat(Pallathadka P., 2025). In the evolving ecosystem of transformation, after the pandemic, SMEs are well placed to be an important contributor in expanding the manufacturing and thereby defence preparedness and export competitiveness of India. Overall, Brazilian and Indian SMEs have been growing strongly (OECD, 2025). However, this opportunity is hindered by the inability of many SMEs to match the pace of technological change because of persistent skill and knowledge gaps across their workforce(A. Kumar, 2025) (R. Patel et al., 2023). Moreover, Indian defence SMEs continue to be constrained in capability to design and develop large defence equipment or critical sub-systems. By engaging in specific functional areas such as materials engineering, communication systems, aerospace technologies and naval application directly with foreign companies, the SMEs can modernize and, in the process, grow themselves up to international standards and capabilities and at some point, the capability gap will be closed (Young & Industry, 2016). Capabilities and weapon systems are increasingly complex and difficult to navigate and SMEs must be able to adjust quickly with effective upskilling and reskilling. As SMEs continue to penetrate the domestic and international value chains, it becomes essential to prepare employees to the defence technology specific learning needs, the adaptive learning solutions required for niche defence production & innovation needs.

1.1.2 *The Challenges in Defence SMEs*

In the last few years, it has been observed that SMEs are slow in digital transformation in spite of the potential benefits from advanced digital-enabled tools, practices and services. (OECD, 2021). Productivity and tech adoption of Indian SMEs lag their peers in emerging and advanced economies. Secondly, India's domestic defence SME space, in its current configuration, maybe hard-pressed to compete with foreign defence majors even for complex contracts, not to speak of servicing the growing needs of the Indian military unless these skill and tech gaps are plugged (S. K. Patel & Tripathi, 2022). Additionally, to retain manpower, SMEs need to continuously upgrade their technical skills through training. Whilst COVID-19 has driven digital transformation for SMEs, the

digital skills deficit may leave growth and performance differentials exposed (NSDC, 2020; OECD, 2021). Supporting training and capacity building through skill upgradation is required for Indian defence SMEs(Young & Industry, 2016) . Defence SMEs need to be nurtured and handholding is recommended for them to be competitive in the defence industry(KPMG et al., 2021). Although the favourable policy exists for the market environment, one of the most important challenges faced by Defence SMEs is the absence of structured and flexible training programs that are required for this sector's constantly changing and technology-based skill demands(Sushil et al., 2022). Traditional training formats generally depend on rigid, one-size-fits-all approaches that do not consider the varied learning profiles, learning styles, and proficiencies of employees. This results in lesser than optimal learning outcomes, low knowledge retention, and limited practical applicability(Pagaduan & Natividad, 2025). In response to this gap, there is a considerable interest in recognition of the potential of Personalised Learning (PL) especially when combined with Emerging Technologies (ETs).

As discussed above, the major obstacle that hinders competitiveness of SMEs is the technology skills gap—especially in emerging domains such as Artificial Intelligence (AI), Big Data, Cybersecurity, digital twin, Internet of Things (IoT), and immersive technologies like Augmented/Virtual Reality. Accordingly, these emerging technologies are increasingly being adopted across Indian defence initiatives, including enhanced AI-enabled surveillance, autonomous systems, cyber defence frameworks, ship building and AR/VR-based training simulators (Varma, 2023). Emerging Technologies (ETs) are classified as complex, disruptive, and contextually adaptive, with the power to reshape learning processes (Neira et al., 2017), (Rotolo et al., 2015). In this light, Personalised Learning (PL) using ETs—like AI, learning analytics, Large Language Models, cloud computing, intelligent tutors, and mobile-based delivery—appears as a potent solution that address individual learning needs of defence SMEs. Research indicates that the integration of such technologies to create adaptive, learner-centric systems improves autonomy, real-time feedback, and job-specific competency enhancement (K. Kumar, 2018) (S. Y. Chen et al., 2016). Therefore, by incorporating Personalised Learning into reskilling initiatives, Indian Defence SMEs can aspore to accelerate workforce readiness, reduce digital capability gaps, and align their human resources with both domestic modernization and global defence export standards.

Personalised Learning systems are known to be modifying content dynamically with respect to content difficulty, format (text, audio, video), and progression based on learners' preferences, present knowledge, and level of present engagement with content (Lee et al., 2020). In the global context, recent studies have shown that personalised learning frameworks in SMEs lead to enhancement in learner engagement, faster skill acquisition, and improved behavioural intention for lifelong learning(Stavropoulos et al., 2021), (Chen et al., 2021).The four-tier framework developed by Stavropoulos et al. advocates AI-based customization, micro-learning modules, regular feedback, along with certain performance analytics—all of which are critical towards transforming training ecosystems. However, it is observed that Indian Defence SMEs are yet to systematically adopt or evaluate such frameworks. There is also a lack of empirical studies mapping the VARK learning styles (Visual, Aural, Read/Write, Kinesthetic) and content preferences of SME employees in the Indian defence sector (Chimalamarri Reddy et al., 2025). This presents a research gap, which this study proposes to address, by developing a learner-aligned, technology-supported personalised learning model.

1.2 Problem Statement

The Indian Defence SME market, has a significant challenge in keeping pace with the evolving tech landscape and rapidly emerging technologies around autonomous systems, drone tech, advance manufacture, cyber-physical systems and digital twin simulations, with skill gaps (Futures, 2023). Many firms lack personnel with the expertise to work with these new technologies, creating a "capability gap" between what modern defence projects require and what these small manufacturers can deliver (S. K. Patel & Tripathi, 2022) . Reskilling and upskilling are the need of hour and Indian

Government also launched multiple initiatives(IBEF), 2023). Non-availability of structured, adaptive, and Personalised training interventions to cater to individual learner may contribute to widen skill gaps. The lack of personalisation leads to disengagement, poor knowledge transfer, and low impact on operational readiness(Bhutoria, 2022) . Despite the promise of adaptive and AI-driven learning models, there is a lack of empirical research in the Indian defence context examining their effectiveness. Specifically, no systematic attempt has been made to evaluate the training effectiveness of personalised learning models which are based on emerging technologies among defence SME employees. Therefore, there is a need to study for fulfilling this gap by identifying employees' learning preferences, develop a personalised learning model using emerging technologies, and evaluate its effectiveness in in holistically enhancing the overall training outcomes. The findings will offer evidence-based guidance for scalable, context-specific training frameworks in Indian Defence SMEs.

1.3 Research Questions and Research Objectives

Research aim is to study the training effectiveness of personalised learning framework adopting emerging technologies among employees of Defence SMEs in Hyderabad, with a focus on personalising content with individual learner preferences and VARK learning styles**.** Based on the aim, the research questions are given below**:-**

RQ1. How has the research evolved on the implementation of Technology-Enabled and Personalised Learning solutions using emerging technologies in Defence SMEs?

RQ2. To what extent do Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI) predict Behavioural Intention to use personalised learning among employees of Defence SMEs?

RQ3. How does Behavioural Intention influence Reaction during the use of personalised learning systems?

RQ4. How does Behavioural Intention mediate the relationship between adoption constructs (PE, EE, FC, SI) and Reaction?

RQ5. How do demographic variables (Gender, Qualification, Experience) and VARK Learning Style Modality moderate the relationships between the adoption constructs and Behavioural Intention?

Based on the above Research questions, Research Objectives are given below: -

RO1. To critically review existing literature on the adoption of Technology-Enabled Learning (TEL) and Personalised Learning using emerging technologies in the context of Defence SMEs.

RO2. To evaluate the influence of key adoption constructs—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI) on Behavioural Intention (BI) to use personalised learning in Defence SMEs.

RO3. To assesses whether Behavioural Intention significantly influences Reaction, thereby determining the effectiveness of personalised learning systems.

RO4. To ascertain the mediating role of Behavioural Intention in the relationship between PE, EE, FC, SI and learners' Reactions.

RO5. To examine the moderating effects of demographic factors **(**Gender, Educational Qualification, Years of Experience) and VARK learning styles on the relationships between PE, EE, FC, SI and Behavioural Intention.

The synopsis is structured into five chapters: Chapter 1 introduces the research context and objectives, while Chapter 2 presents a comprehensive review of relevant literature. Chapter 3 details the research methodology, followed by Chapter 4, which focuses on data analysis and key findings. Chapter 5 concludes the study by summarizing the outcomes and outlining the limitations and directions for future research.

Chapter 2

Literature Review and Theoretical Background

2.1 Overview

This chapter presents the theoretical basis and scholarly discourse underpinning the adoption of Personalised learning in Technology Enabled Learning (TEL) environments, particularly within Indian Defence SMEs. Absence of trained manpower and Entrepreneurship Development Programs (EDPs) along with digital learning are suggested for reducing SME skill gap (Singh & Paliwal, 2017). Further, enhanced collaboration between SMEs and academic institutions would help in addressing both technical and managerial skill deficits(Hattiambire & Harkal, 2022). It is also noted that severe impact of the COVID-19 pandemic on labor availability and the return migration of skilled workers has further widened the skill gap which can be mitigated through training (Sahoo & Ashwani, 2020). Further due to institutional weaknesses in skill delivery, the importance of integrating digital skilling programs into national policies such as Skill India and the NEP 2020 are critically required (Lamba & Jain, 2021). Technology Enabled Learning models are critically required for upskilling and reskilling SMEs. This chapter begins by defining TEL and exploring its notable impact through digital tools that enhance learning delivery, interactivity, and engagement. Emphasis is placed on the emergence of Personalised learning as a central theme in modern TEL, emphasizing its ability to adapt content, pace, and pedagogical strategies based on learner preferences and data. The chapter further explores the potential of adaptive learning models, limitations and reviews key technology adoption frameworks, culminating in a detailed justification for using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the guiding theoretical model for studying personalised learning adoption in Defence SMEs.

2.2 Technology Enabled Learning (TEL)

2.2.1 *Enhancing Learning Through Digital Tools and Personalisation*

Technology-Enabled Learning (TEL) is the use of technology in LMS systems, mobile devices, cloud platforms, AI or multimedia tools to help facilitate and enhance and individualize teaching/learning. (Tiwari, 2024). E-Learning and Personalised learning are included in TEL. TEL includes a wide range of applications which support both formal and informal learning by improving availability, flexibility, learner engagement, and instructional effectiveness (Bates, 2019) (Cárdenas-Robledo & Peña-Ayala). TEL has considerably improved education and training systems by enhancing availability, interaction, and scalability through digital tools. The advances in educational technology, encompassing learning management systems, big data, and analytics, is transforming higher education institutions and enhancing digital change (Kustitskaya et al., 2023). Over the past five years, TEL has been increasingly adopted across multiple diverse sectors, including higher education, SMEs, vocational training, and corporate learning (Ackermans et al., 2025).

2.2.2 *Emergence and Definition of Personalised Learning in TEL*

TEL using diverse adaptive learning technologies, can personalise or customise the learners experience and has a greater learning outcome possibility than traditional classrooms (Albatayneh et al., 2018). The term “Personalised learning” has drawn considerable attention of the researchers since 2008(Shemshack & Spector, 2020) and become a buzzword in the education and TEL. The aim of Personalised learning (PL) is to dynamically adapt a system according to the needs and characteristics of individual students in order to overcome the disadvantages of the “one-size-fits-all” approach in modern learning environments(Xie, 2019). Further, trends were reviewed and growth of adaptive/ Personalised learning including research issues of learning outcomes, the parameters, learning supports, subjects and hardware were elaborated. The rapid advances in ETs have enabled PL to be gradually more adaptive, adaptive learning to be highly Personalised. These differences and

similarities coupled with in-depth analysis of PL and adaptive learning have been investigated(Peng et al., 2019). In literature, these two terms have been considered interchangeably(X. Chen et al., 2021). A four-tier conceptual framework for smart learning, specifically designed for SMEs, highlights the AI-powered learning personalisation, real-time performance analytics, and microlearning modules(Stavropoulos et al., 2021). Personalised Learning systems offer significant advantages in tailoring education to diverse learner needs, improving outcomes and engagement. Their findings support the thesis that scalable PL frameworks could be pivotal in closing skill gaps within Indian MSMEs, particularly when training needs are varied and context-specific (du Plooy et al., 2024). The differences between traditional learning and personalised learning are tabulated below in Table 1.

Table 1. Differences between Traditional Learning and Personalised Learning*

Dimension	Traditional Learning	Personalised Learning
Approach	Instructor-led, curriculum-driven	Learner-centered, need-based and adaptive
Delivery of content	Standardised for all learners	Customized to learner profiles, goals, and preferences
Pacing	Fixed schedule, batch-wise	Self-paced, dynamic progression based on mastery
Engagement	Passive (lectures, notes)	Active (interactive modules, simulations, gamification)
Assessment	End-term tests, same for all	Continuous, adaptive, formative and personalised
Technology Integration	Low (projectors, printed materials)	High (AI, analytics, mobile, AR/VR, adaptive engines)
Skill Retention & Transfer	Dependent on instructor quality and repetition	Reinforced through spaced practice, microlearning, personalisation
Scalable	Limited by trainer bandwidth and scheduling	Scalable across roles, locations, and learning styles
Application in Defence SMEs	May not meet fast-changing skill needs	Enables targeted upskilling dynamic technical environments
Barriers to Adoption	Resistance to new content, logistical challenges	Requires digital readiness, learner data infrastructure

**Source*: Compiled by the author

2.2.3 *Potential of Personalised Learning*

The utility of Personalised adaptive learning has been identified by researchers as a valuable and versatile tool with multiple advantages including enhancements in learning outcomes, student engagement and better quality of learning and improvement in teaching efficiency. Other advantages include its capability improve academic performance, support individual-paced and efficient learning, and decrease anxiety in various subjects (Y. C. Yang et al., 2014), (Deng et al., 2019). Its ability to provide Personalised feedback, promote active and self-regulated learning, and maintain educational continuity, along with increased student satisfaction(Alshalabi I., 2016). This study

presents a compelling case for the adoption of Personalised adaptive learning in various learning environments, with evidence pointing to its potential to improve academic performance, enhance the learning process, and support individual students' needs (T.-C. Yang et al., 2013),(Rosen et al., 2018). While certain papers reported a notable impact on learning, few others reported no influence on Personalised learning on student's learning outcomes and performance. This difference highlights that the effect of Personalised learning may vary depending on how the learning is integrated into a learners wider educational learning experience (du Plooy et al., 2024).

2.2.4 *Limitations and Challenges in Implementation*

Various limitations of Personalised Learning include difficulties in programming and teaching content formulation by instructors, limited learner control over the entire learning process, and the need for high self-regulation among students (Harati et al., 2021),(Clark & Kaw, 2020). Limitations include insufficiencies in the learning system to cater for diverse learner characteristics, resulting in potential effects on the learning outcomes, challenges faced by learners in adapting to various online instructions, and the potential costs(Scarpiello, 2021) . Furthermore, personalised learning used certain data such as page navigation, mouse clicks, and multiple keystrokes which may not consider audio or video data, and the system may not consider learner emotions including frustration and boredom (Scarpiello, 2021). Studies have reported a variety of indicators used as triggers for activating adaptive content delivery, such as students' individual knowledge levels, behaviour and self-rated learning styles or preferences (Putra et al., 2021), (Troussas et al., 2021). Further, cognitive styles, sensory modalities, and dyslexia were utilised to customise learning paths in Personalised learning (Papamitsiou et al., 2020), (Leas, 2015). It is interesting note that time duration of Personalised learning was implemented widely varied across different studies, including online learning revision tutorial and simply the duration of one course (Hinkle et al., 2020),(Latham et al., 2014). The details of personalised Learning along with content-delivery, strengths, limitations and impact on the learner are tabulated in Table 2

Table 2. Data chart on the key characteristics and impact of Personalised Learning*****

Author, Personalised adaptive learning measures	**Content delivered through personalised adaptive learning**	**Strengths of personalised adaptive learning**	**Limitations of personalised adaptive learning**	**Impact on academic performance**
Basitere et al. (2023) None reported	Self-assessment quizzes	Improve learning outcomes and quality of learning; Other: Timely learner feedback & use of visual modes to explain concepts.	Technological limitations; Other: Interactive platforms are expensive and not all learners have prior experience with technology.	Increased learner success
Gransden et al. (2024) Learner engagement based on Learning Analytics (Activity logs/ Clickstreams)	Other: Referencing & learner systems	Personalisation of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation	Technological limitations	Increased learner success

Ipinnaiye et al. (2024) Learner engagement based on Learning Analytics (Activity logs/Clickstreams); Confidence level on content related questions	Academic teaching content	Personalisation and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation	Pedagogical limitations; Logistical limitations	Increased learner success
Papamitsiou et al. (2020) Learner engagement based on Learning Analytics; Pre-knowledge quiz/test; Physiological data; Learner attributes	Self-assessment quizzes	Personalisation and customization of learning; increase engagement and motivation.	None reported	No impact reported
Premlatha et al. (2016) Learner engagement based on Learning Analytics; Multi-modal data; Learning profiles – objective	Academic teaching content	Personalisation and customization of learning.	None reported	No impact reported
Xie et al. (2019) Pre-knowledge quiz/test	Other: English second language - word learning	Personalisation and customization of learning.	Time and resource limitations	Increased learner success
Xu et al. (2014) Pre-knowledge quiz/test	Academic teaching content; Self-assessment quizzes	Personalisation and customization of learning.	None reported	Increased learner success

**Source*: Compiled by the author

2.3 Theoretical Frameworks for Technology Adoption in Personalised Learning

In the field of Information Systems, a range of theoretical frameworks are popularly used, demonstrating the persistent efforts of IS researchers and theorists in validating robustness of the existing frameworks. The theories include Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975), the Social Cognitive Theory (SCT) by Bandura (1986), the Technology Acceptance Model (TAM) by Davis (1986), the Theory of Planned Behaviour (TPB) by Ajzen (1991), the Model of PC utilization (MPCU) by Thompson, Higgins, and Howell (1991), the Innovation Diffusion Theory (IDT) by Moore and Benbasat (1991). Further theories include the Motivational Model (MM) by Davis, Bagozzi, and Warshaw (1992) and the Combined TAM and TPB or C-TAM-TPB by Taylor

and Todd (1995), and lately, Unified theory of acceptance and use of technology (UTAUT) by Venkatesh, Morris, Davis, and Davis (2003) (Gunasinghe et al., 2020). The UTAUT has emerged as a leading model for explaining users' adoption of new technologies, including e-learning platforms(Venkatesh et al., 2003a) . The UTAUT is a comprehensive model to explain user intentions to use information technology and subsequent usage behaviour (Tamilmani et al., 2021) (Soares et al., 2024).

2.3.1 *UTAUT's Relevance in E-Learning Adoption*

UTAUT's value is quite evident in the education and e-learning domain. A systematic review (2024) of about 160 studies in the higher education validated UTAUT to be a major framework with various constructs as determinants of learners' behavioural intentions to utilise educational technologies (L. Xue et al., 2024). The model's different core constructs have been validated multiple times in TEL settings in various contexts and regions. During the COVID-19 pandemic, researchers turned to UTAUT to understand the forced shift to online learning. UTAUT is described as *"the most popular technology acceptance model"* for assessing students' intention to continue using e-learning in a mandatory environment (Patil & Undale, 2023) . UTAUT was applied to Indian college students during the pandemic and found that *performance expectancy, effort expectancy, facilitating conditions,* and related factors were the most significant predictors of e-learning adoption (Nain, 2023). These contemporary studies underscore UTAUT's relevance and reliability in analysing e-learning uptake. Personalised learning systems are technological innovations that must be accepted by users for benefits and UTAUT provides a method to understand the acceptance of Personalised e-learning. Further, research findings reinforce the UTAUT model's ability in explaining student behavioural intentions regarding Personalised learning system adoption in educational environments, with particular focus on Vietnamese higher education(Nguyen & Nguyen, 2024). Thus, UTAUT is well-suited as the theoretical framework for analysing the adoption of Personalised Learning systems in a defence SME environment.

2.3.2 *Core Constructs of the UTAUT Model*

There are four main independent variables which influence acceptance of technology as identified in UTAUT -Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. These result in Behavioural Intention (BI) to use the technology and, consequently, the actual usage and user reaction. The Performance Expectancy, as the extent to which an individual believes that using the system will aid him or her in achieving gains in job performance. This structure repeatedly emerges as the most important predictor of BI in the context of educational technology(L. Xue et al., 2024).Effort Expectancy reflects how easy it is to use the system. In Personalised e-learning, Effort Expectancy is referred to as the degree of ease associated with use which describes the extent to which the learner believes that the platform is navigable and the content accessible (Venkatesh et al., 2003b), (Nain, 2023) . The construct social influence is defined as the perception that the influential people think that the person should use the new system. The social impact component measures the impact of influencing factors on the behaviour of users, such as friends' opinions, or boss' orders (Venkatesh et al., 2003b). A few research papers addressed the issue whether facilitating condition could reduce the obstacles in learning, and then promote the acceptance and use of users.

2.3.3 *Behavioural Intention and Reaction*

In the UTAUT model, Behavioural Intention (BI) to use is the direct precursor of usage. BI expresses the motive of learner or his purpose of using the system. Behavioural intention has been empirically proven to be a powerful predictor of technology use in various research works. Indeed, UTAUT-driven works generally report a very strong association between behavioural intention and self-reported usage. Behavioural intention influenced perceived actual use of a Personalised learning system extensively. UTAUT review stressed that research exists which solely tend to BI as the main

mediator between expectancy and influence constructs on usage of technology(Nguyen & Nguyen, 2024), (L. Xue et al., 2024).

While UTAUT traditionally focuses on usage (behaviour) as the final dependent variable, in an e-learning training context, it is useful to consider training outcomes as well. Donald Kirkpatrick's four-level model of training evaluation is often used to assess training effectiveness. Level 1, "Reaction," refers to the immediate affective response of participants – essentially their satisfaction and perceptions of the training(Hamtini, 2008) . Incorporating the Reaction**,** defined as user satisfaction with the system and content, into the UTAUT has gained strong empirical support in recent literature, particularly in the context of Personalised learning systems. Integrated user satisfaction into an extended UTAUT-ECM model was used to explain academic staff's continued use of GenAI tools, validating that Reaction significantly predicts Behavioural Intention in educational settings (Fayad et al., 2025). Similarly, user perceptions of system training and support—key elements influencing Reaction—directly shape system acceptance in online higher education environments (Soares et al., 2024). Further, a systematic review of augmented reality in training and education, highlighted that satisfaction remains a core determinant of technology acceptance across training interventions (Graser & Böhm, 2024). These findings justify the inclusion of Reaction as a construct within UTAUT, especially for evaluating the training effectiveness and adoption of Personalised learning frameworks in Defence SMEs.

2.3.4 *Limitations of UTAUT*

However, there are limitations to the extent of UTAUT adoption in complex learning environments such as Defence SMEs. With its extensions, however, the model has been criticized for leaving out learner-centric constructs like perceived enjoyment, which are essential in the acceptance behaviour for e-learning. The affective dimension of learning is largely ignored in UTAUT, which reduces the explanatory strength of the theory for educationally focused personalised or adaptive learning systems(Chao, 2019). And in terms of predictor effectiveness, the model did not prove to be very good when work in voluntary use situations where user is not forced to use the system (Dwivedi et al., 2019a).. This restriction is particularly crucial in Defence SMEs, where employee autonomy and role variety are high, making it difficult to consider behavioural intention as a uni-dimensional construct. Moreover, a recent meta-analytic review has reported that Social Influence (SI) and Facilitating Conditions (FC) are two of the fundamental constructs of UTAUT that show conflicting, mixed or low effects in e-learning study settings, implying less relevance of these factors in the digitally matured or policy-regulated organizational settings(Zheng et al., 2025). Another major shortcoming of the model is that it is biased toward performance related variables with little focus on the affective, cultural and organizational factors that also affect technology adoption (Bervell & Umar, 2017). Empirical studies of the model have produced mixed or weak findings across different context such as SMEs, public sector and educational sector (Dwivedi et al., 2019b) (Venkatesh et al., 2016). In addition, it does not consider system-specific attributes such as trust, perception of risk, and usability which are vital within e-learning, healthcare, and financial technology (fintech) domains (Williams et al., 2015). Meta-analyses have criticised the UTAUT model for being too reliant on core constructs and for failing to take sufficient account of the contextual variation, yet reviewers also have neither abandoned the model's utility (Blut et al., 2022),(Dwivedi et al., 2019b). Instead, they argue for situation-specific adaptation. Defence SMEs are, by definition, semi-structured, policy-driven environments in which the adoption of technology is dictated more by the ease of use (EE) and system support (FC) than individual attitude—all areas where UTAUT has evidence of consistency.

2.4 Research Gaps

While India's defence policy increasingly stresses indigenization and SME integration, there is a notable absence of structured, adaptive, and large-scale implementable training frameworks which

are required for the technological realities of defence SMEs. Traditional training models continue to dominate, often ignoring the varied and different cognitive styles, roles, and skill levels of employees, resulting in poor knowledge retention and disengagement. Although emerging technologies such as AI-driven adaptive learning platforms and microlearning modules have been successfully deployed in other sectors, Defence SMEs in India lack empirical studies validating the application, acceptance, and effectiveness of such Personalised learning systems. Moreover, the use of learner-centric pedagogies like VARK (Visual, Aural, Read/Write, Kinesthetic) remains underexplored in this context, despite its proven potential to improve learner engagement and training outcomes in global SME settings (Stavropoulos et al., 2021) , (X. Chen et al., 2021). Although the UTAUT framework has been extensively used to model technology adoption in higher education and corporate learning, its application within Indian Defence SMEs for Personalised e-learning adoption remains under-researched. Particularly, there is a lack of studies that integrate key moderators which are age, experience, qualification, and VARK modality within UTAUT to understand their influence on Behavioural Intention and Training Effectiveness. Furthermore, the extension of UTAUT to include Reaction as a construct which is aligned with Kirkpatrick's model is sound theoretically, but empirically not undertaken in Defence SME contexts. Finally, while several studies validate the effectiveness of Personalised adaptive learning in academic settings, no systematic investigation has been carried out in defence-oriented industrial environments. This study addresses these critical gaps by evaluating training effectiveness of a Personalised learning framework, grounded in UTAUT theoretical framework.

2.5 Conceptualisation and Operationalisation of Constructs

In this section, conceptual definition and operationalization of constructs used in the research and according to UTAUT1 and Kirkpatrick's Level 1 (Reaction) are elaborated. Each construct was measured by a five-point Likert scale and these are validated through research about technology acceptance and e-learning. The operationalization adopts from validated scales modified to employ in defence SMEs in Indian context.

2.5.1 *Performance Expectancy*

In the context of Personalised learning in Defence SMEs, this refers to an employee's belief that using the personalised learning system will enhance their understanding, productivity, and skill levels. The items include perceived improvement in understanding, faster learning, time-saving, job performance enhancement, and skill utility (Patil & Undale, 2023),(L. Xue et al., 2024). Five items (Q1–Q5) adapted from UTAUT and prior e-learning studies were used to measure PE. These include perceived improvement in understanding, faster learning, time-saving, job performance enhancement, and skill utility (Venkatesh et al., 2003b).

2.5.2 *Effort expectancy*

Effort Expectancy refers to "the degree of ease associated with the use of the system" (Venkatesh et al., 2003b). In Personalised learning, it denotes how intuitive and simple the system is perceived to be by the learner, as a result, the amount of cognitive effort that is required can be reduced. Four items (Q6–Q9) measured EE, focusing on ease of learning, system operability, clarity of interaction, and perceived skillfulness in using the system.

2.5.3 *Facilitating Conditions*

Facilitating Conditions refer to "the degree to which an individual believes that an organizational and technical infrastructure exists to support system use" (Venkatesh et al., 2003b). In the e-learning context, it includes availability of technology, user support, and access to resources. Four items (Q10–Q13) were used to assess FC, covering resource access, user knowledge, system compatibility, and support availability.

2.5.4 *Social Influence*

Social Influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003b). In Defence SMEs, this encompasses perceived encouragement or expectations from supervisors, peers, and the general culture of the organization. Four items (Q14–Q17) were adapted to reflect influence from significant others, peers, and perceived societal value of using Personalised learning tools. Prior validation of similar constructs can be found in various studies(Liangyong Xue et al., 2024) (Al-Rahmi et al., 2022).

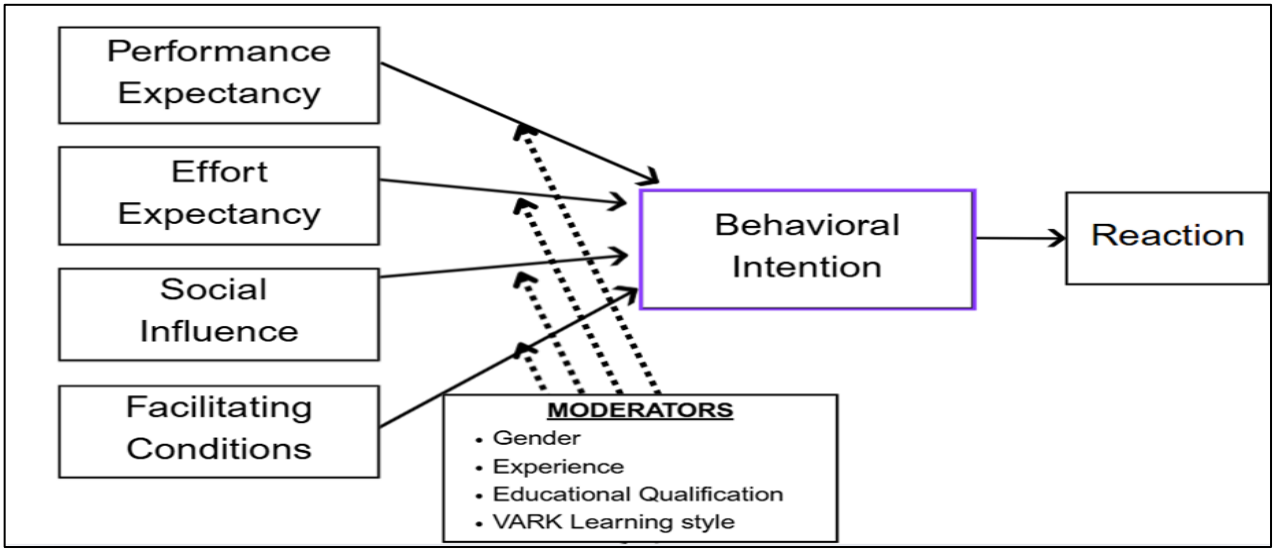
2.5.5 *Behavioural Intention*

Behavioural Intention represents "a person's conscious plan or motivation to use the technology in the future" (Venkatesh et al., 2003b). In this study, it captures the willingness of Defence SME employees to adopt and continue using the Personalised learning system. Four items (Q18–Q21) were used to measure BI, capturing intention, planning, value perception, and prediction of system usage. This construct is instrumental as it serves as a mediator between the independent variables (PE, EE, SI, FC) and the outcome variable (Reaction), supported by recent e-learning acceptance research (L. Xue et al., 2024).

2.5.6 *Reaction*

Reaction, as defined in Kirkpatrick's Level 1 of training evaluation, refers to "the degree to which participants find the training favorable, engaging, and relevant" (Kirkpatrick, 2006) (Rafiq, 2015). It indicates immediate learner satisfaction and affective response toward the training. Five items (Q22–Q26) were designed to capture perceptions of time-value, usefulness, knowledge gained, ease of following, and overall effectiveness of the Personalised learning experience. Reaction is considered the dependent outcome, influenced by BI, and used to assess the training effectiveness(Harris et al., 2020). The proposed conceptual framework is illustrated in Fig 1.

Fig 1. Proposed Conceptual Framework



2.6 Hypotheses Development

2.6.1 *Performance Expectancy and Behavioural Intention*

Performance Expectancy in the context of Personalised learning in Defence SMEs denotes an employee's belief in the fact that the use of a learning system facilitates comprehension, increases productivity and raises competence levels. The perceived improvements in understanding, learning,

time-efficiency, job performance, skill applicability are constituents of PE and are measured with five items, which are adapted from the UTAUT and from previous studies on e-learning. These consist of perception of increased comprehension, acceleration of learning, saving of time, job performance and utility of skill. Xue et al. (2024) stressed that users' belief in system effectiveness significantly influences their intent to use adaptive learning platforms. Patil and Undale (2023) reported that perceived usefulness was the most influential factor in continued e-learning engagement. Therefore, the following hypothesis is proposed:

H1*: Performance Expectancy (PE) has a positive and significant influence on Behavioural Intention (BI) to use personalised learning.*

2.6.2 *Effort Expectancy and Behavioural Intention*

Effort Expectancy (EE) has been widely studied as a critical determinant of Behavioural Intention (BI) in technology acceptance models, particularly UTAUT. It captures the perceived ease of use and clarity in system interaction. Lower perceived effort increases the likelihood of technology adoption, especially in early stages of system use. In Personalised learning contexts, mostly among employees with different levels of digital competence and literacy in Defence SMEs—ease of use becomes a fundamental acceptance factor. The findings of Patil and Undale (2023) further support this finding by showing that systems requiring minimal cognitive effort increase willingness to participate in digital learning environments. Given this theoretical foundation and evidence-based support, the following hypothesis is proposed:

H2*: Effort Expectancy (EE) has a positive and significant influence on Behavioural Intention (BI) to use personalised learning.*

2.6.3 *Facilitating Conditions and Behavioural Intention*

Facilitating Conditions (FC) are frequently identified as enablers of user adoption in technology acceptance research. While FC is traditionally considered a direct predictor of actual use behaviour, several studies have extended its influence to Behavioural Intention (BI)—particularly in organizational and training environments where usage is optional. Strong organizational support, clear vision communication, and infrastructure readiness significantly increased staff's intention to adopt and engage with LMS-based learning platforms (Veseli et al., 2025). Nguyen and Nguyen (2024) similarly reported that institutional support and ease of access were strong antecedents of behavioural intention in smart learning environments. The presence of accessible learning infrastructure encourages continuous learner participation (Al-Rahmi et al., 2022). Based on these findings, the following hypothesis is proposed:

H3*: Facilitating Conditions (FC) have a positive and significant influence on Behavioural Intention (BI) to use personalised learning.*

2.6.4 *Social Influence and Its Impact on Behavioural Intention*

Social Influence (SI) represents the extent to which an individual perceives that important others— such as colleagues, supervisors, supervisors, or authority figures—believe they should use a particular system (Venkatesh et al., 2003b). Managerial encouragement and team-based expectations significantly improved employees' intentions to engage with digital learning platforms(Alshammari & Qtaish, 2019) . Similarly, it is observed that peer influence and leadership endorsement positively influenced the adoption of Personalised LMSs (Nguyen & Nguyen, 2024). Further learners were more likely to adopt e-learning tools when their social context actively supported and validated such use(L. Xue et al., 2024) . Given the collective nature of learning environments in Defence SMEs and the importance of perceived endorsement, the following hypothesis is proposed:

H4*: Social Influence (SI) has a positive and significant influence on Behavioural Intention (BI) to use personalised learning.*

2.6.5 *Linking Behavioural Intention to Learner Reaction in Personalised Learning*

Behavioural Intention (BI) is a widely accepted antecedent to both actual system use and affective user outcomes in technology acceptance research. Reaction denotes the learner's instant emotional response and satisfaction- consistent with Level 1 of Kirkpatrick's training evaluation framework (Ruiz & Snoeck, 2018) (Hamtini, 2008). Although UTAUT primarily models BI as a predictor of actual usage, several scholars have extended this to include affective reactions and learner experience—especially in training and education contexts. Users with stronger behavioural intention are likely to have more favorable reactions to learning systems (Arslankara et al., 2024), (Harris et al., 2020). This satisfaction is a reflection of prior motivation, active engagement, and expectation alignment as well. Evaluating Reaction as an outcome variable provides valuable knowledge into learner-centered interventions and enables early-stage feedback. In environments where structured feedback is less and motivation may be extrinsically driven, further understanding how intention affects learner satisfaction can help towards constructing a more streamlined instructional design and strategies. This link is further supported by recent empirical studies that higher behavioural intention translated into better learner satisfaction scores in adaptive LMS environments. Motivational intention to use a system positively influenced user reaction and perceived training value in organizational settings (Abbad, 2021). Hence, the following hypothesis is posited to better understand the motivational–emotional linkage in Personalised learning:

H5*: Behavioural Intention (BI) has a positive and significant effect on Reaction during the use of personalised learning system.*

2.6.6 *Independent factors (PE, EE, FC, SI), Behavioural Intention and Reaction*

In models of technology adoption and training effectiveness, Behavioural Intention (BI) is typically situated as a mediator between external determinants of behaviour (e.g., Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence) and user outcomes (e.g., satisfaction, system use, performance). Although the UTAUT initially placed BI in a predictive role toward actual use, several extensions and contextual adaptations have shown its mediational role in downstream learning and emotional experience of e-learning environments. The learner's reaction to the system (in terms of learner satisfaction, engagement, perceived value) in a Personalised learning in Defence SMEs' setting is formed not just by the system attributes but also by the user's motivational intention to use it. Behavioural intention serves as a filter that determines how individuals perceive and internalize learning experiences psychologically (Harris et al., 2020). Without the willingness to use a system, even the best-designed tools may not translate into positive learner reactions.

The recent research findings provide support for the mediating effects of BI on the relationship between core UTAUT determinants (PE, EE, FC, and SI) and training satisfaction (Alblooshi & Abdul Hamid, 2022) . In the same vein, Nguyen and Nguyen (2024) showed that BI mediated the psychological passage of user expectations, support perceptions, and peer influence into positive system perceptions. Direct effects from PE or EE on satisfaction weakened when BI was included in the model—highlighting its central mediating function(L. Xue et al., 2024). Testing this hypothesis is critical to understanding how intention translates system expectations into emotional outcomes, and is especially relevant in Defence SMEs where reaction and motivation drive both short-term satisfaction and long-term learning behaviour. It helps in determining if/whether system features are effective as well as determine if system features have meaningful impact on learner engagement due to motivation alignment. Accordingly, the following mediation hypothesis is proposed:

***H6**: Behavioural Intention (BI) mediates the relationship between the Independent Variables—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI)—and Reaction during use of personalised learning.*

2.6.7 *Moderating Role of Demographic Factors in Technology Adoption*

In technology acceptance studies, demographic variables including gender, education, years of experience are often tested as moderators that enhance or diminish the relationship between predictor variables and behavioural intention. The UTAUT model of Venkatesh et al. (2003) made gender and experience as moderating factors and argued that user background may also influence how users understand system usefulness, effort, social context and support structures. In the case of personalised learning in Defence SMEs, this issue is particularly important because of the diverse learners. Such a diverse set of "commuters" would have a wide range of prior experience with digital tools, formal education, and career experience, which, in turn, might influence their perceptions of utility, usability, and system support. For example, older employees may regard performance outcomes as more important, whereas younger employees may regard effort expectancy to be more important. In a similar vein, higher levels of education may lead individuals to be more independent, which may render the effect of social influence weaker, while the opposite might apply to low-educated individuals for whom peer cues or available support are stronger.

This moderating perspective has been empirically backed by recent studies. Gender influenced sensitivity to social factors in LMS adoption (Patil & Undale, 2023). Moreover, educational background moderated learner engagement and intention in AI-driven adaptive training platforms(Nain, 2023). Testing the moderating effect of these demographic variables allows for better targeting of training interventions and platform design in Defence SMEs. Therefore, the following hypothesis is posited:

***H7**: Demographic factors (Gender, Educational Qualification, Years of Experience) significantly moderate the relationship between the independent variables—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI)—and Behavioural Intention to use personalised learning.*

2.6.8 *Moderating Effect of VARK Learning Styles on Technology Adoption*

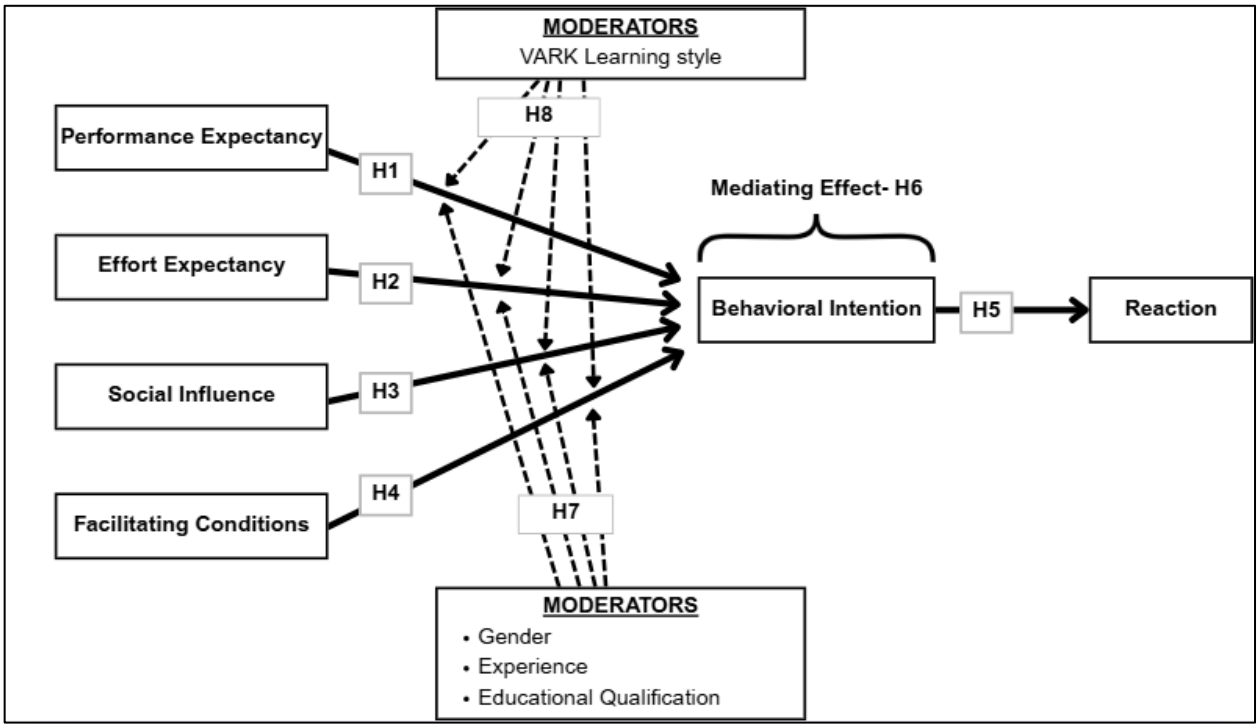
The VARK model categorizes learners based on their choices for Visual, Aural, Read/Write, and Kinesthetic modalities, providing a well-constructed structure for adapting and aligning learning outcomes to individual needs(Newbury, 2024). While this model is frequently used to personalise instructional content in educational systems, its role as a moderating variable in technology acceptance frameworks remains largely untested. Existing literature indicates that modifying and developing content with learner modality improves motivation and cognitive engagement (Tortorella & Graf, 2017) (Shah, 2021), but no conclusive evidence has been established on whether such preferences statistically alter the strength of relationships between system beliefs and behavioural intention.

Nguyen and Nguyen (2024) found that learners with varied modality preferences responded differently to system features such as ease of use and interface adaptability. Similarly, Xue et al. (2024) observed enhanced engagement when learning systems dynamically accommodated user choices and preference in it. However, none of these studies statistically tested moderation effects of learning styles in structural models like UTAUT. This research addresses that gap by examining whether VARK modality—classified into unimodal, bimodal, trimodal, and quadrimodal learners—moderates the influence of Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI) on Behavioural Intention (BI) to use Personalised learning. In Defence SME settings, where learners are diverse in age, background, and cognitive

preference, is important for expandable and inclusive system design. Therefore, the following hypothesis is proposed:

H8*: The VARK learning style modality significantly moderates the relationship between the independent variables—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI)—and Behavioural Intention to use personalised learning. Various hypotheses proposed above are illustrated in the Fig 2 below.*

Fig 2. Proposed Conceptual Model with Hypotheses



Chapter 3

Research Methodology

3.1 Research Design and Methodological Approach

Research design is the foundation of the entire research process and influences the logical design of conditions for data collection, measurement, and analysis in such a way as to help achieve the research objectives (Sekaran & Bougie, 2022). It is the framework that links research questions to empiric data and, ultimately, to valid conclusions. A sound research design is particularly important in management and social sciences because it increases the internal validity and the reliability of the study so that the study's findings can be replicated and be taken seriously (Saunders et al., 2019). This paper employs a deductive, non-experimental multi- cross sectional research design to explore research objectives based on hypothesis testing. The work adopts a quantitative deductive approach in which hypotheses drawn from established frameworks such as UTAUT and Kirkpatrick's evaluation model were tested through empirical testing. Objective conclusions were made from the data observed using a structured questionnaire with statistical modeling techniques. The study was guided by the proposed conceptual framework and theoretically driven deductive logic was used to ensure that all phases of the study remained theory driven.

3.2 Sampling Design

Sampling design refers to the deliberate scheme or plan used by the researcher to select a part of the population under study in which to carry out research or data collection.

3.2.1 *Population of the Study*

Towards this study, Study population comprises of all employees of defence SMEs at Hyderabad and all employees of defence SMEs working for DPSU/DRDO/Defence Units at Hyderabad. The sampling unit refers to the individual employees within these Defence SMEs who are potential users, facilitators, or evaluators of personalised learning systems. These individuals form the basis for data collection and hypothesis testing in this study.

3.2.2 *Sampling Technique*

A non-probability sampling technique such as purposive sampling is used and it is a systematic plan where respondents are chosen according to pre-specified criteria regarding the research question of interest (Saunders et al., 2019). Also, referred to judgmental or selective sampling, it relies on the knowledge of the researcher to select the respondents who can provide the most informative inputs (Sekaran & Bougie, 2022). Given the specialized and access-controlled operational environment of Defence Small and Medium Enterprises (SMEs), this study adopted a non-probability purposive sampling strategy to ensure the selection of informed and relevant participants. Defence SMEs function under layers of confidentiality, regulatory oversight, and mission-critical operations, which preclude the possibility of deploying random sampling methods. It allowed the study to gather rich, context-specific insights that random sampling may have failed to elicit, particularly given the complex and varied digital maturity levels across different defence SMEs. To operationalize this strategy, the researcher conducted field visits and held discussions with key institutions and stakeholders. In Hyderabad, extensive interactions were carried out with Defence Public Sector Undertakings (DPSUs), DRDO laboratories, and SME directors registered with these units. Further access and respondent identification were facilitated through Defence Indigenisation Cells, MSME development organizations, and the SME Association of Hyderabad, which maintain updated rosters of actively contributing vendors in the defence ecosystem. Additionally, information and support were obtained from the Headquarters of the Indian Navy, Army, and Air Force, which helped in locating SMEs involved in component manufacturing, system integration, and service provisioning

under defence offset and procurement schemes. This layered and purposive outreach ensured that the sample included respondents who could provide reliable inputs regarding personalised learning adoption in the defence SME sector.

3.2.3 *Sampling Frame*

The sampling frame for this study comprises employees of Defence Small and Medium Enterprises (SMEs) operating in and around Hyderabad**,** identified through a verified list drawn from Naval Headquarters, New Delhi**,** as well as affiliated records from DRDO laboratories and Defence Public Sector Units (DPSUs) based in Hyderabad. The listed SMEs represent a diverse ecosystem, ranging from firms offering basic defence-related services and components to those engaged in advanced manufacturing of complex electronic and mechanical systems. These enterprises actively contribute to the defence supply chain by fulfilling contractual obligations for DPSUs, DRDO labs, and Indian Defence Forces.

3.2.4 *Sample Size Determination*

The sample size to determine the users of Personalised Learning from Defence Small and Medium Enterprises at Hyderabad by using the Cochran's (1977) formula of variability. Due to the heterogeneous nature and high variability characteristics of the elements of the population, the formula of variability has been used to calculate the sample size. The following formula has been used to determine the sample size when the population is having high degree of variability:
$n = [z^2pq]/[e^2]$ where, n is the sample size, z is the selected critical value of desired confidence level, p is the estimated proportion of an attribute that is present in the population, $q = 1- p$ and e is the desired level of precision or tolerable error. Assuming the maximum variability, which is equal to 50% ($p =0.5$) and taking 95% confidence level with ±5% precision, the calculation for required sample size will be as follows—

$p = 0.5$ and hence $q =1-0.5 = 0.5$; $e = 0.05$; $z =1.96$
$n = [z^2pq]/[e^2] = [(1.96)^2 (0.5) (0.5)]/[(0.05)^2] = [(3.8416) (0.25)/[0.025]$
$n = 384.16$ (rounded to 384)
In this research work the sample size has been 400.

3.3 Data Collection procedure

3.3.1 *Primary Data*

The primary data required for the research was collected using the survey method with a detailed self-administered questionnaire among the respondents to study Performance Expectancy, Effort Expectancy Facilitating conditions, Social Influence Behavioural Intention and Reaction for Training Effectiveness of Personalised Learning.

3.3.2 *Secondary Data*

Sources of secondary data for the study included the national and international journals, research articles, books, newspapers, research reports by reputed agencies and online data sources related to the Training Effectiveness of Personalised Learning.

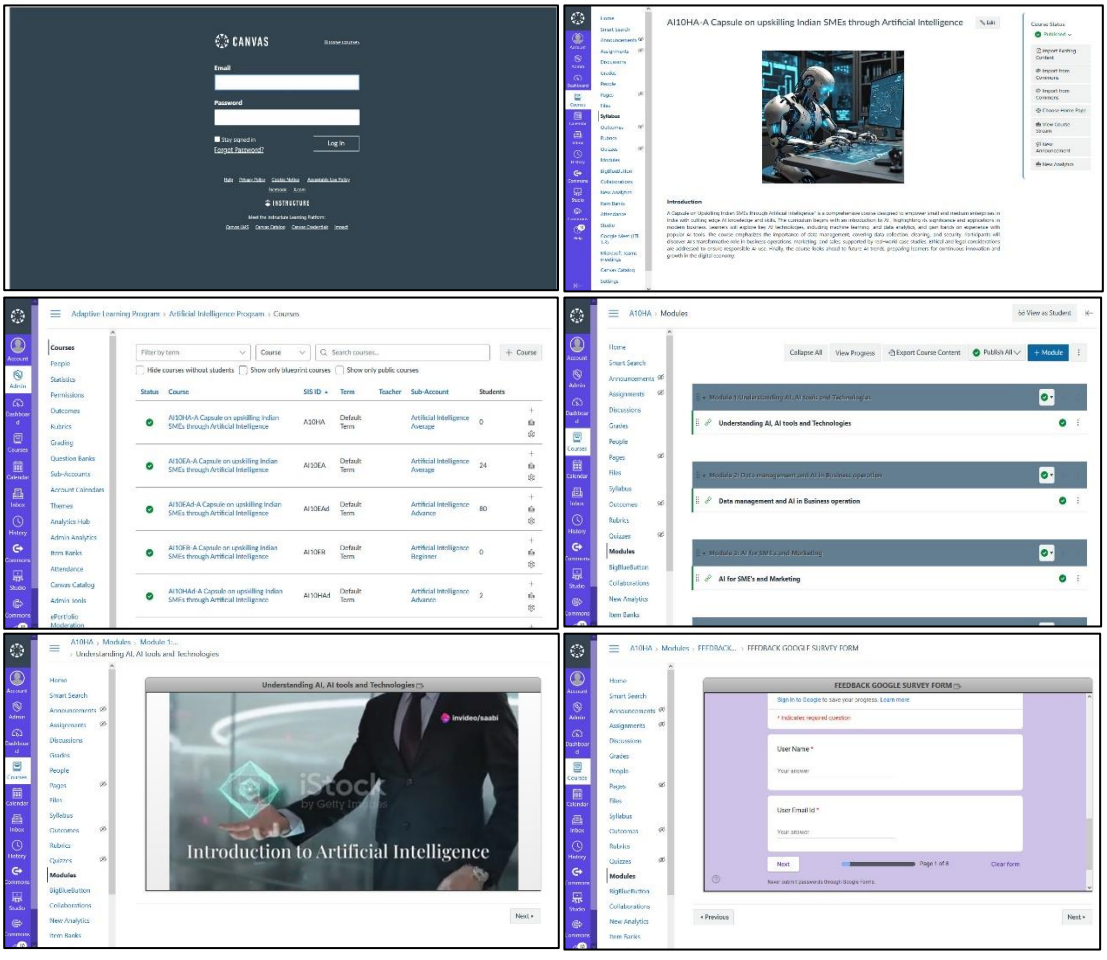
3.3.3 *Phased Research Implementation Strategy*

To ensure methodological robustness and capture both progression and impact across various stages of learning the study was designed in five interlinked phases, each representing a cross-sectional view at a specific stage of intervention: -

Phase 1 – Demographic and Learner Preference Mapping
Initial data collection focused on capturing demographic variables (gender, qualification, experience) and identifying individual VARK learning styles (unimodal, bimodal, trimodal, quadrimodal) using a standardised self-assessment tool. This enabled learner profiling to inform instructional customization.

Phase 2 – Personalisation of Learning Content
Based on Phase 1 insights, learning content was adapted based on learner preferences and VARK learning styles. Canvas Learning Management System (LMS) is widely regarded as one of the world's leading platforms for online education. Canvas offers a rich set of features that made it ideal for the research in uploading personalised content as per Learner Preferences and VARK learning Style. The Personalised learning approach supported by Canvas LMS begins with learners choosing their preferred language and duration of the video. A diagnostic quiz assessed the learner's proficiency level, categorized as beginner, average, or advanced. Further, based on the VARK Questionnaire attempted by the learner, he was categorised as V, A, R, K or combination of the preferences. Based on this evaluation, the content was adapted and presented in Canvas, ensuring learners receive material suited to their skill level and preferred learning style. This Personalised approach promotes engagement and effective learning without overwhelming or under-challenging the user. This implementation was supported by Edvanta Technologies, an official Canvas LMS partner in India. With deep expertise in both Canvas and Moodle platforms, Edvanta is known for building large-scale learning ecosystems for academic and corporate. Few screenshots of Canvas LMS, adapted for the Personalised Learning for Defence SMEs are placed below in Fig 3:

Fig 3. Screenshots of LMS

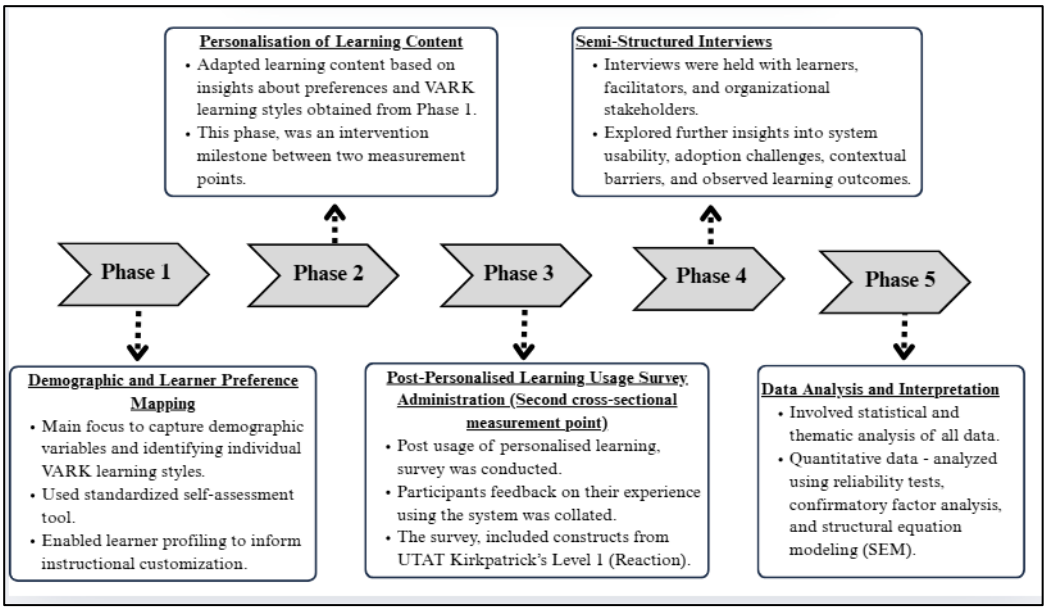

CANVAS
AI10HA-A Capsule on upskilling Indian SMEs through Artificial Intelligence
Introduction to Artificial Intelligence
FEEDBACK GOOGLE SURVEY FORM

Phase 3 – Post-Personalised Learning Usage Survey Administration
After the respondents have used the personalised learning, a structured survey was conducted to collate various participants feedback on their experience using the Personalised learning system. The survey included validated constructs from UTAUT (PE, EE, FC, SI, BI) and Kirkpatrick's Level 1 (Reaction). This constituted the second cross-sectional measurement point.

Phase 4 – Semi-Structured Interviews
To support quantitative data, semi-structured interviews were held with learners, facilitators, and organizational stakeholders. These explored further insights into system usability, adoption challenges, contextual barriers, and observed learning outcomes. In all the above phases, given the access-controlled and hierarchical nature of Defence SMEs, additional care was taken to safeguard respondent identity and organizational confidentiality, upholding the standards of data privacy and ethical rigor required in defence-affiliated research environments.

Phase 5 – Data Analysis and Interpretation
The final phase involved statistical and thematic analysis of all data. Quantitative data were analysed using reliability tests, confirmatory factor analysis, and structural equation modeling (SEM). The process is diagrammatically represented in Fig 4.

Fig 4. Sequence of Phases in Data Collection


Personalisation of Learning Content
• Adapted learning content based on insights about preferences and VARK learning styles obtained from Phase 1.
• This phase, was an intervention milestone between two measurement points.
Semi-Structured Interviews
• Interviews were held with learners, facilitators, and organizational stakeholders.
• Explored further insights into system usability, adoption challenges, contextual barriers, and observed learning outcomes.
Phase 1
Phase 2
Phase 3
Phase 4
Phase 5
Demographic and Learner Preference Mapping
• Main focus to capture demographic variables and identifying individual VARK learning styles.
• Used standardized self-assessment tool.
• Enabled learner profiling to inform instructional customization.
Post-Personalised Learning Usage Survey Administration (Second cross-sectional measurement point)
• Post usage of personalised learning, survey was conducted.
• Participants feedback on their experience using the system was collated.
• The survey, included constructs from UTAT Kirkpatrick's Level 1 (Reaction).
Data Analysis and Interpretation
• Involved statistical and thematic analysis of all data.
• Quantitative data - analyzed using reliability tests, confirmatory factor analysis, and structural equation modeling (SEM).

3.4 Validity and Reliability

To ensure measurement rigor, both content validity and face validity of the questionnaire were established prior to field deployment. A structured validation process was undertaken by consulting academic and domain experts familiar with personalised learning systems and Defence SME training contexts. The draft questionnaire was reviewed and refined based on expert feedback received during in-person consultations at two academic institutions: *College of Defence Management (Osmania University) and JBIMS, Mumbai University and* domain experts from DPSUs/SMEs. The experts assessed the relevance, clarity, and representativeness of the questionnaire items in capturing the theoretical constructs drawn from UTAUT, Kirkpatrick's model, and VARK modalities. Based on their feedback, terminology was contextualized, a few redundant items were removed, and select items were reworded for improved clarity and coherence with the Defence SME setting. This process ensured that the instrument was well reasoned and relevant contextually, thereby strengthening its

content validity. Further, the reliability of the instrument was assessed using Cronbach's alpha and Composite Reliability (CR) during the data analysis phase, confirming the internal consistency of each construct.

3.5 Pilot Study

To ensure improved clarity, consistency, and relevance to the context of the survey instrument, a pilot study was conducted with a sample of 50 respondents drawn from employees of Defence SMEs in Hyderabad. This pre-test was necessary for validation of the instrument's suitability prior to full-scale deployment. The selection of 50 participants for pilot testing is supported by several academic recommendations. A pilot sample size of 30 to 50 respondents is sufficient to detect issues related to item ambiguity, wording, survey flow, and instrument fatigue(Van Teijlingen & Hundley, 2001). Similarly, a minimum of 30 participants is adequate for preliminary reliability testing and item refinement when conducting social science research(Johanson & Brooks, 2010).

3.6 Analysis of Pilot Study

Before formal pilot testing, the questionnaire was pretested with a small group of Defence SME professionals (n=10) to assess the clarity, language, and the flow of the items. Feedback received was used to refine question wording, scale options, and sequence. A pilot test was then conducted with 50 respondents from the population to verify the structure and reliability of the instrument. Using Cronbach's Alpha, all six constructs (Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Behavioural Intention, and Reaction) demonstrated reliability coefficients above 0.8, indicating strong internal consistency. The results are tabulated below in Table

Table 3. Summary of Pilot Study - Reliability Statistics

Variables	Cronbach's Alpha (α)
Performance Expectancy	0.820
Effort Expectancy	0.817
Facilitating Conditions	0.817
Social Influence	0.819
Behavioural Intention	0.809
Reaction	0.824

Chapter 4

Data Analysis and Findings

4.1 Overview

Data analysis has been classified into Descriptive analysis & Inferential Analysis. The data has been analysed by using IBM SPSS Statistics Version 25.

4.2 Demographic data analysis

For doing the descriptive analysis, the simple percentage method has been used to calculate the frequencies. Inferential analysis has been used to derive the logical conclusions of the samples. Multiple Regression and Structural Equation Modelling (SEM) was used for the same. Demographic characteristics of the sample are given in Table 2.

Table 4. Demographic Representation of SME sample employees

Demographic Information	Categories	Frequencies	Percentage
Gender	Male	317	79.25
	Female	83	20.75
	Total	**400**	
Age group	30 years and below	222	55.5
	31 to 40 years	89	22.25
	41 to 50	56	14
	Above 50 years	33	8.25
	Total	**400**	
Educational Qualification	Under graduate	47	11.75
	Graduate	227	56.75
	Post Graduate	126	31.5
	Total	**400**	
Work Experience	5 years and below	217	54.25
	6 to 10 years	71	17.75
	11 to 20 years	67	16.75
	Above 20 years	45	11.25
	Total	**400**	
Language you prefer for training/ online courses	Hindi	41	10.25
	English	359	89.75
	Total	**400**	
Preferred duration	About 5 minutes	211	52.75
	About 10 minutes	189	47.25
	Total	**400**	
Standard of Knowledge	Beginner	39	9.75
	Average	114	28.5
	Advanced	247	61.75
	Total	**400**	
VARK Learning style	Unimodal	25	6.25
	Bimodal	124	31
	Trimodal	138	34.5
	Quadrimodal	112	28
	Total	**400**	

Source: Primary Data

4.3 Normality of Data

The dataset was subjected to a normality assessment to ensure its suitability for multivariate analysis, specifically through the evaluation of Skewness and Kurtosis for each item. Based on statistical analysis, the absolute values of Skewness and Kurtosis for all measured items remained within the acceptable thresholds recommended by Kline (2011)—that is, skewness within ±3 and kurtosis within ±10. Accordingly, the data is deemed suitable for further analysis using Maximum Likelihood Estimation (MLE) techniques in SEM.

4.4 Statistical Tools for Data Analysis

The data were analysed using Microsoft Excel, IBM SPSS Statistics (Version 25), and IBM SPSS AMOS (Version 25) for Structural Equation Modeling (SEM). SPSS Statistics was used for reliability and exploratory analysis, while AMOS (Analysis of Moment Structures) supported confirmatory factor analysis and path modeling. The selection of IBM SPSS AMOS for Structural Equation Modeling (SEM) with a sample size of 400 is methodologically justified based on established academic guidelines and best practices in multivariate analysis. SEM is particularly appropriate for testing complex theoretical models with multiple relationships between latent constructs, allowing simultaneous examination of measurement and structural models while accounting for measurement error (Byrne, 2016), (Hair et al., 2019). The inclusion of Behavioural Intention as a mediator, and the examination of both direct and indirect effects between constructs like Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Reaction, necessitated a robust, multivariate technique capable of assessing both measurement and structural models concurrently. concurrently. The sample size of 400 exceeds the minimum requirements recommended by leading SEM scholars, with Hair et al. (2019) suggesting a minimum of 200 cases, Byrne (2016) recommending 200-400 cases for most applications, and Boomsma (1982) identifying 400 cases as optimal for stable parameter estimates (Boomsma, 1982; Hair et al., 2019). This methodological approach enables comprehensive assessment of convergent and discriminant validity through factor loadings and Average Variance Extracted (AVE), reliability evaluation through Composite Reliability, and robust hypothesis testing through path analysis with standardised coefficients, ensuring the research meets rigorous academic standards for structural equation modeling.

4.5 Data Analysis

4.5.1 *Descriptive statistics*

Frequencies, means, and SD were the descriptive statistics used in the current study. Table 2 below displays the descriptive statistics namely Mean and SD for the study variables. Mean and standard deviation of items of various constructs are given in Table 3.

Table 5. Mean and Standard Deviation

Construct	Items	Mean	Std. Deviation
		3.8	**0.61**
	PE1	3.775	0.636
Performance Expectancy	PE2	3.71	0.672
	PE3	3.825	0.574
	PE4	3.905	0.525
	PE5	3.7825	0.641
		3.79	**0.58**
Effort Expectancy	EE1	3.9175	0.604
	EE2	3.78	0.547

	EE3	3.8725	0.659
	EE4	3.8425	0.52
Facilitating Conditions		**3.84**	
	FC1	3.727	0.724
	FC2	3.852	0.664
	FC3	3.9	1.052
	FC4	3.885	0.606
Social Influence		3.746	0.974
	SI1	3.557	0.893
	SI2	3.662	1.318
	SI3	3.927	1.014
	SI4	3.84	0.6712
Behavioural Intention		**3.79**	**1.178**
	BI1	3.72	1.269
	BI2	3.737	1.231
	BI3	3.92	1.008
	BI4	3.785	1.205
Reaction		**3.833**	**0.973**
	REE1	3.755	1.011
	REE2	3.917	1.062
	REE3	3.78	0.89
	REE4	3.872	0.862
	REE5	3.842	1.039

4.5.2 *Refinement of Measurement Model Evaluation*

The measurement model was initially assessed using Confirmatory Factor Analysis (CFA) to evaluate the validity and reliability of latent constructs as per the original UTAUT framework. However, the initial CFA results indicated poor model fit, with several indices (e.g., RMSEA, CFI) failing to meet recommended thresholds (Hu & Bentler, 1999). In response, a diagnostic review was conducted that involved identifying outliers and items with low factor loadings (<0.6), which were systematically removed to improve model specification. This step aligns with best practices in SEM literature, which recommend iterative purification to enhance construct validity (Hair et al., 2019).

Despite these modifications, the revised model continued to show suboptimal fit, suggesting misspecification or construct instability. Consequently, the model was re-evaluated using Exploratory Factor Analysis (EFA) to reassess the underlying factor structure without imposing the original theoretical constraints. EFA indicated a more stable five-factor solution, representing Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Behavioural Intention (BI), and Reaction (REE). Importantly, all items associated with Social Influence (SI) demonstrated significant cross-loadings across multiple constructs, indicating lack of discriminant validity. Based on both statistical evidence and theoretical reasoning—particularly the policy-driven nature of training adoption in Defence SMEs, where social pressure is likely minimized—the SI construct was dropped from the final measurement model.

This iterative approach to model refinement is consistent with empirical SEM practices, particularly in under-researched domains such as Defence SME learning systems, where construct behaviour may diverge from established patterns (Byrne, 2016; Lowry & Gaskin, 2014). The final five-construct model achieved acceptable fit indices and reflected both empirical robustness and theoretical coherence, thus providing a valid foundation for subsequent structural path analysis.

4.5.3 *Model Fit Analysis*

Table 6 below presents the key goodness-of-fit indices obtained from the measurement model analysis. The values achieved fall within the acceptable thresholds recommended by Hu and Bentler (1999), indicating that the proposed model fits the data adequately. These results collectively support the adequacy of the measurement model, confirming its suitability for subsequent structural path analysis.

Table 6. Goodness-of-Fit Indices for Measurement Model

Fit Index	Value	Threshold	Interpretation
SRMR	0.049	< 0.08	Good fit
CFI	0.918	≥ 0.90	Acceptable fit
GFI	0.990	≥ 0.90	Excellent fit

4.5.4 *Convergent Validity and Construct Reliability Assessment*

Table 7 presents a summary of standardised factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for each latent construct included in the measurement model. All constructs demonstrated adequate convergent validity, with AVE values exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981). The construct of Performance Expectancy (AVE = 0.649) and Effort Expectancy (AVE = 0.803) showed particularly strong convergent validity, supported by high loading values across their respective items. Composite Reliability values ranged from 0.792 (Facilitating Conditions) to 0.938 (Behavioural Intention)**,** indicating excellent internal consistency across constructs. The consistently high standardised loadings (mostly above 0.70) further support the measurement accuracy and internal coherence of the constructs. These results, given in Table 7, confirm the construct reliability and convergent validity of the questionnaire, thereby reinforcing the measurement model's robustness for structural analysis.

Table 7. Standardised factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR)

Construct	Items	Standard Estimate	AVE	Composite Reliability
Performance Expectancy	PE2	0.793	0.649	0.870
	PE3	0.817		
	PE4	0.682		
	PE5	0.843		
Effort Expectancy	EE1	0.969	0.803	0.886
	EE2	0.799		
Facilitating Conditions	FC1	0.902	0.517	0.792
	FC2	0.855		
	FC3	0.583		
	FC4	0.611		
Behavioural Intention	BII1	0.838	0.795	0.938
	BII2	0.919		
	BII3	0.910		
	BII4	0.908		
Reaction	REE2	0.830	0.748	0.898
	REE3	0.849		
	REE4	0.931		

Note. AVE, Average Variance Extracted

4.5.5 *Discriminant Validity (HTMT Analysis)*

To assess discriminant validity, the Heterotrait-Monotrait (HTMT) ratio of correlations was examined. As recommended by Henseler et al. (2015), HTMT values below 0.90 are indicative of adequate discriminant validity, while more conservative thresholds set this cutoff at 0.85. The HTMT values for all construct pairs in this study ranged from 0.404 (PE–BI) to 0.701 (EE–BI), all of which fall well below the 0.85 threshold. This confirms that each construct is empirically distinct from the others. Particularly, constructs such as Performance Expectancy (PE) and Behavioural Intention (BI) exhibited low cross-correlation (HTMT = 0.404), while Effort Expectancy (EE) and Behavioural Intention (BI), despite showing the highest value (HTMT = 0.701), still maintained acceptable distinctiveness. These results, tabulated in Table 6, support the conclusion that the model exhibits strong discriminant validity, justifying the use of these constructs in subsequent structural analysis.

Table 8. Heterotrait-Monotrait (HTMT) ratio of correlations

Constructs	PE	EE	FC	BI	REE
PE	1.000				
EE	0.432	1.000			
FC	0.483	0.451	1.000		
BI	0.404	0.701	0.508	1.000	
REE	0.517	0.637	0.406	0.542	1.000

4.5.6 *Multicollinearity*

Multicollinearity occurs when two or more variables are highly correlated to each other. Different values were suggested to be satisfactory by different scholars . For instance, correlations up around 0.8 or 0.9 is considered highly problematic, while a value 0.7 or higher is considered reason for concern(Pallant, 2010) ,(Tabachnick & Fidell, 2007). The presence of multicollinearity is determined by two values: tolerance and VIF. (Variance Inflation Factor) (Pallant, 2010). If the value of tolerance is greater than 0.10 and VIF value less than 3.0, then there is no multicollinearity. To ensure the reliability of regression coefficients in the Structural Equation Model (SEM), multicollinearity was assessed among the independent constructs: Performance Expectancy (PE), Effort Expectancy (EE) and Facilitating Conditions (FC). Variance Inflation Factor (VIF) was computed for each predictor. VIF values quantify how much the variance of a regression coefficient is inflated due to multicollinearity. In this study, all VIF values for PE, EE and FC were below the accepted threshold of 5, indicating no serious multicollinearity. Specifically, the VIF values ranged from 1.34 to 1.52

4.6 Structural Model Evaluation and Hypothesis Testing Results

The structural equation model (SEM) was evaluated to examine the predictive relationships among the key latent constructs: Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Behavioural Intention (BI), and Reaction (REE). The overall model demonstrated an acceptable fit. The model chi-square was significant (CMIN = 588.129, df = 109, $p < .001$), the chi-square/df ratio was 5.396, indicating moderate fit and the Comparative Fit Index (CFI = 0.909).

The path estimates revealed that Effort Expectancy ($\beta = 0.651$) and Facilitating Conditions ($\beta = 0.195$) had significant and positive effects on Behavioural Intention (BI) ($p < .001$). In contrast,

Performance Expectancy (β = 0.043) did not have a statistically significant effect on BI (p = 0.349), suggesting that ease of use and supportive conditions are more influential in shaping user intentions than perceived usefulness in this context. BI was found to be a strong predictor of Reaction (REE) with a standardised estimate of 0.606, reinforcing its role as a mediator and key outcome construct in training effectiveness. The squared multiple correlations (R^2) were also notable: BI was explained by 62% of the variance (R^2 = 0.620), while REE was explained by 37% (R^2 = 0.368). These values demonstrate a reasonably strong explanatory power of the model for user intention and satisfaction.

4.6.1 *Unstandardised Regression Weights*

The following table presents the unstandardised regression weights extracted from the AMOS output. These weights indicate the raw (unscaled) influence of the independent constructs on the dependent constructs in the structural model. Unstandardised and standardised regression weights indicated in Table 9 and Table 10.

Table 9. Unstandardised Regression Weights

Path	Estimate	S.E.	Critical Ratio (C.R.)	p-value
BI ← PE	0.088	0.094	0.936	0.349
BI ← EE	1.247	0.094	13.213	***
BI ← FC	0.333	0.081	4.091	***
REE ← BI	0.442	0.034	12.887	***

Note: "*" indicates p < 0.001**

Table 10. Standarised Regression Weights

Path	Standardised Estimate (β)	p-value	Significance
PE → BI	0.043	0.349	Not significant
EE → BI	0.651	< 0.001	Significant
FC → BI	0.195	< 0.001	Significant
BI → REE	0.606	< 0.001	Significant

R^2 for Behavioural Intention (BI) = 0.620

R^2 for Reaction (REE) = 0.368

4.7 Hypothesis Testing Table (Unstandardised Path Estimates)

The table below presents the unstandardised path estimates from the structural model. These values indicate the raw influence of the independent variables on the dependent variables, as measured in their original units. Hypotheses were evaluated based on the significance (p-value) of the regression weights as depicted in Table 11.

Table 11. Unstandarized Regression Weights and Hypothesis validation

Hypothesis	Path	Estimate (β)	S.E.	C.R.	p-value	Supported?
H1A	PE → BI	0.088	0.094	0.936	0.349	No
H2A	EE → BI	1.247	0.094	13.213	***	Yes
H4A	FC → BI	0.333	0.081	4.091	***	Yes
H5A	BI → REE	0.442	0.034	12.887	***	Yes

Note: "*" indicates p < 0.001**

4.7.1 *Mediation Analysis of Behavioural Intention Using SEM*

The mediation effect of Behavioural Intention (BI) was tested using Structural Equation Modelling (SEM), examining whether BI acts as an intermediary in transmitting the influence of the independent variables—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI)—to the outcome variable, Reaction (REE). The overall model fit was found to be acceptable: CMIN/DF = 4.719, CFI = 0.925, IFI = 0.925, and RMSEA = 0.097, indicating moderately good fit and model adequacy, as indicated in Table 12.

Table 12. Mediation Path Analysis Summary

Independent Variable	Direct Effect on REE	Effect on BI	BI → REE	Mediation Type	Supported?
Effort Expectancy (EE)	0.616***	1.213***	0.092†	Partial Mediation	Yes
Performance Expectancy (PE)	0.379***	0.063 (NS)	0.092†	No Mediation	No
Facilitating Conditions (FC)	0.026 (NS)	0.344***	0.092†	Full Mediation	Yes

Note: *** p < 0.001, † p ≈ 0.066 (10% level), NS = Not Significant

4.7.2 *Mediating Role of Behavioural Intention*

The results offer nuanced support for Hypothesis H6A. According to Baron and Kenny (1986), mediation is broadly of two types: complete mediation and partial mediation. When an independent variable no longer influences the dependent variable and the entire effect is transferred on mediating variable after fulfilling all the above conditions, this is known as complete mediation. Partial mediation occurs when the effect of an independent variable on the dependent variable is reducing with the introduction of mediating variable. Behavioural Intention fully mediates the relationship between Facilitating Conditions and Reaction, and partially mediates the relationship between Effort Expectancy and Reaction. In contrast, Performance Expectancy influences Reaction directly, and no evidence was available to evaluate the mediating role of BI in the context of Social Influence. These findings reinforce the critical role of BI in translating ease of use and support into effective user reactions, while perceived usefulness (PE) appears to impact reaction more directly. Mediation

effects provide important theoretical and practical insights into how personalised learning technologies are adopted and experienced by users.

4.7.3 *Moderation Analysis Summary*

This table presents the results of moderation analysis assessing whether Gender, Educational Qualification, Experience, and VARK Learning Style Modality influence the relationship between the independent variables—Performance Expectancy (PE), Effort Expectancy (EE), and Facilitating Conditions (FC)—and Behavioural Intention (BI) to use personalised learning. Moderation was tested via interaction terms in multiple regression analysis through MS excel. The moderation analysis results reveal that none of the interaction terms for Gender, Educational Qualification, Experience, or VARK Learning Style Modality were statistically significant ($p > 0.05$). This indicates that the effects of the independent variables (Performance Expectancy, Effort Expectancy, and Facilitating Conditions) on Behavioural Intention are consistent across different demographic groups and learning style modalities. These findings support the robustness and generalizability of the structural model, suggesting that the influence of key constructs on intention to use personalised learning remains stable regardless of individual background characteristics.

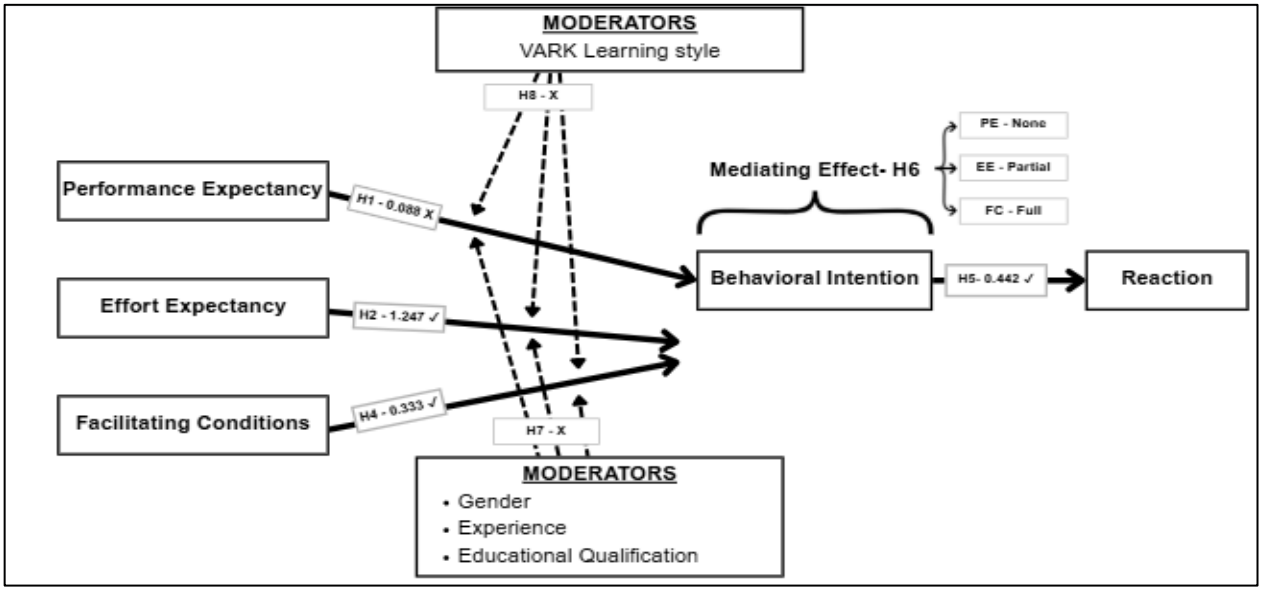
Table 13. Moderation by Gender, Educational Qualifications, Experience and VARK Learning Style Modality

Moderator	Interaction Term	Coefficient	p-value	Significant?
Gender	PE × Gender	-0.1022	0.6665	No
Gender	EE × Gender	0.0561	0.7857	No
Gender	FC × Gender	-0.0426	0.8175	No
Qualification	PE × Qualification	0.0713	0.6236	No
Qualification	EE × Qualification	-0.0912	0.4717	No
Qualification	FC × Qualification	0.1022	0.4051	No
Experience	PE × Experience	0.1101	0.2656	No
Experience	EE × Experience	-0.0512	0.5313	No
Experience	FC × Experience	0.0600	0.4142	No
VARK Modality	PE × VARK	-0.1156	0.2772	No
VARK Modality	EE × VARK	0.0880	0.3141	No
VARK Modality	FC × VARK	0.0174	0.8338	No

4.8 Comprehensive Structural Model

A comprehensive model depicting the results obtained with respect to different relationships is as shown in the Fig 5.

Fig 5. Comprehensive Model with Hypotheses



Chapter 5

Discussions and Conclusions

5.1. Overview

This chapter presents an objective wise discussions, implications, limitations and future scope. The findings of the present study are aligned with and supported by contemporary research in the fields of Technology-Enabled Learning (TEL), Personalised Learning, and user adoption of emerging educational technologies.

5.2 Objective wise Discussions

5.2.1 *Objective 1: To critically review existing literature on the adoption of Technology-Enabled Learning (TEL) and Personalised Learning using emerging technologies in the context of Defence SMEs.*

The first objective sought to critically review the current state of research on the adoption of Technology-Enabled Learning (TEL) and Personalised Learning using emerging technologies in Defence SMEs. Recent literature (Gupta & Sharma, 2024; Kumari et al., 2023) has underscored a rising trend in the use of adaptive and AI-driven learning platforms in higher education and corporate sectors. The literature review has been presented in the second chapter. However, there is a noticeable lack of focus on Defence SMEs, particularly in India. This gap confirms the relevance and necessity of context-specific research as addressed in this study.

5.2.2 *Objective 2: To evaluate the influence of key adoption constructs—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI) on Behavioural Intention (BI) to use personalised learning in Defence SMEs.*

The second objective involved assessing how key constructs—Performance Expectancy (PE), Effort Expectancy (EE) and Facilitating Conditions (FC)—influence Behavioural Intention (BI) to adopt personalised learning. Social Influence (SI) had cross loadings with other factors in measurement model and had been omitted. Recent studies (Tajuddin et al., 2024; Alshammari et al., 2023) validate the significance of EE and FC, with results showing that learners give more weightage to ease of use and system support. The path estimates revealed that Effort Expectancy ($\beta = 0.651$) and Facilitating Conditions ($\beta = 0.195$) had significant and positive effects on Behavioural Intention (BI) ($p < .001$). In contrast, Performance Expectancy ($\beta = 0.043$) did not have a statistically significant effect on BI ($p = 0.349$), suggesting that ease of use and supportive conditions are more influential in shaping user intentions than perceived usefulness in this context. Performance expectancy and social influence were not significant in the final model in a study using UTAUT to predict multigenerational tablet adoption practices(Magsamen-Conrad et al., 2015).

5.2.3 *Objective 3: To assesses whether Behavioural Intention significantly influences Reaction, thereby determining the effectiveness of personalised learning systems*

Behavioural Intention (BI) significantly influenced learners' Reactions ($\beta = 0.606$, $p < 0.001$), validating its role as a key determinant of learning experience and active engagement. This is consistent with empirical findings from adaptive TEL environments (Cheng & Lai, 2023; Arora et al., 2024), where behavioural intention strongly predicts usage satisfaction and behavioural outcomes. The result highlights the importance of motivational constructs in learner-centric systems.

5.2.4 *Objective 4*: *To ascertain the mediating role of Behavioural Intention in the relationship between PE, EE, FC, SI and learners' Reactions.*

The fourth objective tested whether BI mediates the relationship between the independent variables (PE, EE, FC, SI) and Reaction. Mediation analysis showed partial mediation in the EE →

REE path and full mediation for FC → REE. Similar patterns are seen in recent studies where BI mediates use of technology and respective training results (Yusof et al., 2023; Das & Rani, 2022). These results reinforce that usability and support mechanisms translate into satisfaction primarily through intention, while the perceived usefulness (PE) alone does not guarantee meaningful user engagement.

5.2.5 *Objective 5: To examine the moderating effects of demographic factors (Gender, Educational Qualification, Years of Experience) and VARK learning styles on the relationships between PE, EE, FC, SI and Behavioural Intention.*

This moderation analysis was originally planned to be conducted using Multi-Group Structural Equation Modelling (MGSEM). However, this could not be completed due to practical limitations—specifically, unequal subgroup sizes and the complexity of such modelling within the available research timeline. As a result, MGSEM was conceptualized, however not pursued. Instead, a preliminary moderation analysis was carried out using interaction terms in Microsoft Excel. This approach tested whether demographic factors (Gender, Educational Qualification, Years of Experience) and VARK learning styles influenced the relationship between the adoption constructs (PE, EE, FC, SI) and Behavioural Intention. The findings revealed no statistically significant moderation effects, suggesting that these background variables did not meaningfully alter the strength of the core relationships in the model. This finding supports the notion of designing accessible to all TEL systems that work uniformly across various demographic factors. Contrary to expectations, a no moderating role of age was found on the relationship between certain constructs perceived usefulness and Behavioural intention. Similarly, role of gender did not affect the relationship between perceived ease of use and BI, and educational level did not moderate the relationship between perceived usefulness or Quality of Work Life and BI(Tarhini et al., 2014).

5.3 Implications

This research adds multiple contributions to the understanding of how the technology is adopted in personalised learning within Indian Defence SMEs:

5.3.1 *Contribution to Theory*

5.3.1.1 *Understanding Performance Expectancy Construct in Structured Work Environments*

The insignificance of Performance Expectancy (PE) in influencing Behavioural Intention (BI) questions the conventional assumptions of UTAUT in highly procedural domains like Defence. Unlike sectors, where the perceived performance gains drive technology adoption, these findings suggest that in Defence SMEs—which have typical characteristics multiple compliance-bound national and international standards, and non-standard digital literacy—Effort expectancy and facilitating conditions are important. This supports contextual reinterpretation of UTAUT constructs, validating the requirement for personalised learning models in stricter standard compliance-based SMEs. Additionally, results of study of factors influencing Behavioural Intention of Online Learning education of military training in Sri Lankan revealed that Performance Expectancy has insignificant effect. Further, the following studies in Table 14 have indicated weaker impact of PE on BI. In defence environments, these dynamics are even more pronounced, strengthening the interpretation of PE as context-sensitive.

Table 14. Insignificant effect of Performance Expectancy on Behavioural Intention

Study	Sample Size	Country	PE-BI	User Type
Shaqrah& Almara,2022	400	Taiwan	0.064	Students
Subasinghe, 2024	100	Sri Lanka	0.044	Military Officers
Wut et a.,2022	113	Hong Kong	0.084	Students
Khalid et al.,2021	490	Thailand	-0.047	Students

5.3.1.2 *Limited Influence of Social Influence Construct in Defence SMEs*

The exclusion of Social Influence (SI) due to cross-loadings indicated that Social Influence is a weak predictor of Personalised Learning in Defence SMEs. This aligns with research that in generationally diverse, policy-regulated workplaces, the top-down nature of adoption supersedes peer or supervisor influence. It widens our understanding of how SI should be operationalised or possibly replaced in future adaptations of the UTAUT framework within Defence or similarly compliance-based domains. Similarly, the use of e-government systems was a personal and individual issue and not affected by social influence. Venkatesh et al. (2003) reported that the usage of a system depends on the user's beliefs, rather than on others' opinions or advice. Few examples are tabulated below in Table 15.

Table 15. Insignificant effect of Social Influence on Behavioural Intention

Study	Sample Size	Country	SI-BI	User Type
Udeozor et al.,2023	125	Europe	0.082	Students
Meet er al.,2022	483	India	0.075	Students
Mujalli et a.,2022	222	Saudi Arabia	0.004	Students Faculty
Bervell et al.,2022	163	Malaysia	-0.085	Students

5.3.1.3 *Extending UTAUT with Kirkpatrick's Reaction Level in Defence SME*

By integrating Reaction (REE) as a training outcome connected to Behavioural Intention construct, this study improves the understanding of framework by bridging adoption theory (UTAUT) with learning evaluation models (Kirkpatrick Level 1). The significant path from BI → REE confirms that Behavioural Intentions predicts usage and learner satisfaction including engagement (Gajendragadkar et al., 2024). This empirical backing for BI→REE signifies a valuable theoretical-bridge between intention models and experiential educational results. This integration of behavioural intention models (UAUT) with learning evaluation frameworks (Kirkpatrick) represents what Venkatesh et al. (2016) term "theoretical bridging" - combining disparate but complementary theoretical domains to create more comprehensive explanatory models(Venkatesh et al., 2016). Personalised Learning required multi-perspective to understand technological and pedagogical aspects.

5.3.1.4 *Mediation of BI in Reaction*

The analysis of full mediation in the FC → REE path and partial mediation in EE → REE stressed the theory that Behaviour Intention acts as a mechanism through which technological ease and infrastructure translate into satisfaction. This aligns with the idea indicating that Facilitating Conditions are not adequate —internal commitment is essential to extract its benefits(Yusof et al., 2008). These mediation effects enhance the analysis of how constructs interact within UTAUT-based models. Similarly, Dwivedi et al. (2019), in their meta-review of adoption models, highlight the mediating role of psychological constructs like intention in converting enabling conditions into usage satisfaction and learning impact(Dwivedi et al., 2019).This mediation dynamic is also consistent with Khechine et al. (2014), who applied the UTAUT model to webinar use and noted that facilitating conditions had indirect effects on satisfaction via behavioural intention (Khechine et al., 2014). It also aligns with Venkatesh et al.'s (2016) vision of "theoretical bridging", wherein UTAUT is extended to account for affective outcomes like learner reaction (Venkatesh et al., 2016).

5.3.1.5 Novel Integration of VARK with Personalised Learning in Defence SME

A key contribution of this study lies in the connecting VARK learning style model within the framework of Personalised Learning (PL). This was specifically custom made for employees of

Defence SMEs. In Phase 1, learner preferences were systematically identified using the standardised VARK questionnaire, categorizing respondents into unimodal (Visual, Aural, Read/Write, or Kinesthetic), bimodal, trimodal, or quadrimodal learners. Further, customized learning content was delivered, aligning with the learner's dominant modality. This adaptive delivery mechanism moves beyond a one-size-fits-all approach, operationalizing personalisation. In subsequent phases, the adoption of this PL system was empirically tested using the Unified Theory of Acceptance and Use of Technology (UTAUT), where Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence served as antecedents to Behavioural Intention (BI). BI was further modeled as a mediator, influencing the learner's immediate Reaction—mapped as Level 1 of the Kirkpatrick model. By embedding VARK-based adaptive delivery into a technology acceptance framework and linking it to early-stage training output, this study extends UTAUT's application and provides a model for evaluating Personalised Learning adoption in less-explored domains like Defence SMEs.

5.3.2 *Contribution to Practioners*

5.3.2.1 *Higher importance to Effort Expectancy and Facilitating Conditions*

Since Effort Expectancy (EE) and Facilitating Conditions (FC) have demonstrated a significant influence on Behavioural Intention (BI), practical interventions must prioritize user-centric system design and context-specific operational support.

From the standpoint of TEL designers, this requires the creation of intuitive, user-friendly interfaces that reduce the cognitive load and ensure easy interaction, particularly under different constraints typical of defence environments. Systems must be adaptive to user roles, allowing high-skill engineers to access advanced configurations while ensuring low-exposure operators—common in Indian Defence SMEs—can perform essential tasks.

From SMEs view point, the deployment of personalised learning solutions may address infrastructural differences, intermittent connectivity, and changing digital literacy. Platforms may be optimized for offline capability, easy access, and modular learning formats that align with workplace routines. Furthermore, Defence SMEs operate under different skill demographic, with both technically trained engineers and field staff often engaged in non-digital processes. Thus, training modules must be visual, voice-assisted, and language-localized, aligning with the multimodal preferences of such workforces. Facilitating Conditions can be enhanced by installing necessary learning software within the existing digital ecosystems of DPSUs and SMEs, using familiar hardware interfaces, and enabling on-demand, low-bandwidth content delivery.

Ultimately, a successful TEL deployment in Defence SMEs depends on designing with users in the loop, balancing technical features with operational realism, and building confidence through consistent usability, technical support, and targeted user training. Armed Forces, DRDO Labs and DPSUs may encourage development and adoption of Personalised Learning in not only Defence SME but also in their respective environments.

5.3.2.2 *Designing for Motivation to Drive Engagement*

The observed strong association between Behavioural Intention and Reaction indicates the importance of cultivating intrinsic learner motivation—not through compliance-based mandates, but through engaging, contextually aligned learning experiences.

From the perspective of TEL designers, this required connection of adaptive learning pathways, gamified modules, and interactive elements that reinforce relevance and autonomy. The goal is to design systems that respond dynamically to user behaviour, providing timely support, clear

performance information, and personalised learning directions matched with professional roles in Defence SMEs.

For SME users, especially those operating within the Indian Defence ecosystem, the importance of training content to real-world tasks is vital. Employees are more likely to engage when learning systems are perceived as directly applicable to their roles—whether they are engineers working on complex EW systems or technicians managing assembly-level tasks. Techniques, such as progress badges, simulation-based assessments, or mission-based learning flows, can help improve motivation and reaction-level outcomes, particularly in high-discipline environments where routine training fatigue may be observed.

From the standpoint of SME employers—including DRDO labs, DPSUs, and Defence contractors—the focus must be on ensuring learner satisfaction and system use within broader digital upskilling programs. This includes feedback loops in the platform, allowing both learners and trainers to assess progress, find gaps, and customise content. Adaptive support mechanisms not only improve satisfaction (Reaction) but also help align Behavioural Intention with long-term learning objectives, confirming that investments in TEL yield tangible capability development within Defence SMEs.

5.3.2.3 *Understanding the Role of Social Influence*

Social Influence is generally less important in SMEs—and particularly in Defence SMEs—because technology adoption is typically driven by formal directives, hierarchical decision-making, and protocols rather than effect of peers. In such structured environments, users are more influenced by top-down directives and system availability than by colleagues' opinions or social media.

From the perspective of TEL designers, the minimal influence of Social Influence on Behavioural Intention suggests a need to shift design priorities away from peer-based nudging features (e.g., social learning, peer rankings) toward enhancing system usability, and convenience of learning infrastructure. In organised environments like Defence SMEs, user motivation is more likely to be influenced by institutional clarity, formal mandates, and technology reliability than by co-worker endorsements. Designers should therefore focus on giving clear instructions, system notifications, and command-level messaging within platforms to increase adoption.

For SME users, especially in the Defence context, training is often mandatory, scheduled, and standardised, reducing differences in how new technologies are perceived across roles. This is further reinforced by the finding that demographic characteristics such as gender, educational qualification, experience, and even VARK learning styles did not moderate the adoption process. Such uniformity indicates that employees across the organization experience technology in a relatively homogeneous manner, driven more by institutional design than by individual preference.

SME employers, which include organizations like DRDO, DPSUs, and Defence contractors, may interpret these findings as an opportunity to streamline TEL implementation. Rather than focusing on peer-driven influence campaigns, they should give priority to good infrastructure deployment, official communication strategies, and policy-aligned rollout courses. This direction ensures organizational culture alignment where top-down instructions are more effective than informal peer networks. Furthermore, it makes the training strategy simple—designing for a common user base rather than highly personalised demographic segments—leading to cost-effective, scalable learning solutions across Defence SMEs

5.3.3 *Contribution to Research Methodology*

5.3.3.1 *Contextual Application of UTAUT in a Non-Conventional Domain of Defence SMEs*

The current study broadens the study of the UTAUT within the hitherto unexamined context of Defence SMEs, characterised by bureaucratic structures, compliance focused processes, and centralised training. This is important because in contrast to contexts such as consumer markets or educational institutions for which UTAUT has been rigorously tested (Venkatesh et al., 2016), Defence SMEs operate in a distinctive terrain. In doing so, the study provides an empirical confirmation of the utility of the UTAUT framework in this non-standard, low openness setting regulated by confidentiality protection and compliance. It displays that even in settings where peer influence and individual choices are minimized, core constructs such as Effort Expectancy and Facilitating Conditions remain influential. This aids in the theoretical applicability of UTAUT and informs domain-specific learning, chiefly for Personalised Learning solutions in defence-oriented SME ecosystems.

5.3.3.2 *Training Outcome Measures with Adoption Constructs*

This study contributes to the theoretical evolution of technology adoption research in a number of important respects, and notably within a structured and high conformity environment, as are Defence SMEs that deploy Personalised Learning technologies. The present research extends the generalizability of UTAUT beyond behavioural intention in traditional contexts, by treating Kirkpatrick's Level 1 (Reaction) as a dependent variable. Although UTAUT has been shown to predict BI, it has been criticized for its lack of emphasis on post-adoption affective outcomes (Harris, 2019). By connecting BI, and other critical adoption factors, such as Effort Expectancy and Facilitating Conditions, with learner reaction, this study presents an outcome-based explanation model. This is especially relevant in Defence SMEs, where the usage of a mandated system needs to result in a positive experience in terms of learning engagement, satisfaction and operational readiness. The combined model does not only describe use intention, but also users' emotional and perceptual responses to the TEL experience, thereby reflecting institutional training contexts more appropriately (Bilal, 2023).

5.3.3.3 *Robust Structural Equation Modelling with Moderators and Mediation*

The use of SEM to test mediating and moderating effects is a more comprehensive way of understanding the complex relations between variables in the TEL adoption context. While the moderation effects (e.g., gender, experience, and learning styles) were not statistically significant, the methodological model offers a strong methodological analogy for investigating intricate dynamic construct dynamics that have been comparatively under-researched such as Defence SMEs. This layered methodology not only increases the robustness of the empirical validation but also furthers TEL adoption research in structured and policy driven fields.

5.4 Conclusion

In conclusion, this study enriches our understanding concerning TEL and Personalised Learning adoption in Indian DEF SMEs, spanning theoretical, empirical and practical spheres. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and extended with the inclusion of Kirkpatrick's Reaction Level and VARK learning styles, this research aims to deliver a complete model that is designed to suit the structured, compliance-based nature of Defence SME environments. It reveals important subtleties, such as the weak influence of Performance Expectancy and Social Influence, and also demonstrates that Effort Expectancy and Facilitating Conditions play a more influential role in determining Behavioural Intention. These results demonstrate that human-center designs and operational assistance is more important than some perceived performance gain in this case. Also, the strong BI → REE relationship confirms the importance of learner motivation

and system engagement for variance in early-stage TEL effectiveness, broadening the scope of the UTAUT from intention to actual learner experience.

This research also adds methodologically to the extant research by specifying and testing mediation mechanisms, and the direct and indirect effects of adoption constructs within a Defence SME context. The innovative use of Reaction as an affective outcome measure coupled with the use of VARK-driven adaptive content is an early-stage example of fusing technology adoption models with learner centred design. The study proves that Behavioural Intention is not merely a predictor of usage; it is also essentially a mediator that operates between the utilization perspectives of system usability and infrastructure and learner success. The lack of a mediating role for demographic and sensory learning preferences in adoption pathways further supports the argument in favour of scalable, universally-designed TEL systems in Defence contexts. In conclusion, the research offers a domain-specific, theoretically-informed and empirically-validated conceptualization that may inform future TEL design, deployment and evaluation within India's contested defence innovation ecosystem.

5.5 Limitations of the Study

Although this research offers useful and necessary insights into the effectiveness of training of Personalised learning systems in Defence SMEs based on UTAUT, several limitations should be considered.

The first limitation of the study is that it was restricted to Defence SMEs in Hyderabad, hence the generalisability of the findings to other geographical areas, as well as other defence sectors such as DPSUs, DRDO and military training establishments, is limited. Regional socio-cultural environments, operational ecologies and policy parameters can have an impact on preparedness of organization, technology use behaviour and attitude of learner (Zheng et al., 2025) . For example, SMEs in other defence corridors may vary in digital infrastructure maturity, confidence of leadership, and exposure to new technologies. As such, the results offer valuable knowledge on technology-facilitated personalised learning in defence SMEs based in Hyderabad, and caution should be used in generalising the results to the wider national MSME eco-system without further empirical testing in other regions and organizational settings.

Second, the use of cross-sectional data does not allow for the establishment of causality between the independent variables and the outcomes of training. Although strong correlations were demonstrated, the time-varying pattern of the Development of Behavioural Intention and Reaction was not satisfactorily depicted. While significant associations were observed, the temporal dynamics of how Behavioural Intention and Reaction evolve could not be adequately captured. A longitudinal research design would have provided greater insight into causal pathways and the stability of learners' acceptance and responses over time, thereby enhancing the robustness of the model's explanatory power(Hair et al., 2021) .

Third, although Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence were measured through valid instruments in UTAUT, the later construct (Social Influence) was not taken into account because of its cross loadings, thus indicating that cultural or organizational factors may influenced its role in this environment. This constricts the generalization of the UTAUT model.

Fourth, since the study was based on self-reported data from structured questionnaires, self-report biases (e.g., social desirability bias and acquiescence bias) of the response may have been introduced, leading to responses that were simply favorable or pleasing rather than completely accurate (Podsakoff et al., 2003). These biases may impact the construct validity of measures, particularly those used in attitude and behaviour research. Additionally, the lack of longitudinal user behaviour data as found in real interaction logs from Technology Enhanced Learning (TEL)

platforms limits the perspectives on the sustained user engagement and long term performance of the personalised learning system. Incorporating real-time system usage metrics would have offered a more objective and dynamic understanding of learner behaviour over time.

5.6 Future Scope of Research

The paper offers a theoretical foundation for investigating the use of personalised learning by incorporating the VARK learning styles and the UTAUT constructs in the context of Defence SMEs. Based on these results, a number of areas for future research are suggested:

5.6.1 *Wider Geographic and Sectoral Coverage*

The present study was restricted to Defence SMEs in Hyderabad. Further research may widen the geography driven of the study to the Defence SMEs in other Indian defence corridors for example Tamil Nadu, Uttar Pradesh and Gujarat. This will increase the representativeness of the sample and increase the transferability of the findings to the wider SME Defence ecosystem.

5.6.2 *Incorporation of Longitudinal Data*

To examine the development of Behavioural Intention and Reaction over time, longitudinal research should be conducted. This would allow for more robust statements of causation and understanding of the sustainability and long-term effects of personalised learning interventions.

5.6.3 *Integration of Real-time Usage Analytics*

Future research should integrate real learner interaction data from TEL systems (e.g., usage logs, time on task, and module completion). This will allow triangulation of self-report measures and a less subjective insight into student engagement.

5.6.4 *Exploration of Moderating Variables*

Although this research examined VARK learning styles as moderating variables, other potential moderators, for example, organizational culture, digital maturity, or leadership support could be further explored to enhance the explanatory capability of our model.

5.6.5 *Policy and Training Design Implications*

Moreover, future studies may identify PPP models that embed adaptive learning technologies in defence skilling programmes, thus warranting extendibility, cost efficiency and reconciliation with national defence modernization objectives. This kind of cross-sectoral collaboration would also foster a culture of data in workforce training, facilitating skill upgradation in a fast-changing technological environment.

5.6.6 *Model Enrichment through UTAUT Extensions and Contextual Adaptations*

Further research might try to reinsert the Social Influence (SI) construct, but within a situationally-adapted Defence SMEs context, where the peer support at the workplace and the thus adapted command structure may exert different influences on technology adoption than in commercial environments. Furthermore, further investigation may include other extended UTAUT2 constructs such as Hedonic Motivation, Habit, and System Trust to enhance the model's explanatory merits. These models account for emotional and experiential aspects of technology use, aspects that might be particularly pertinent when measuring user engagement and long-term commitment to personalised learning platforms in defence learning contexts.

5.6.*7 Integration of Emotional Intelligence into AI-Powered Personalised Learning*

A promising area for future study in Defence SME training is incorporation of emotional intelligence (EI) markers in AI-enhanced personalised training environments. Here, Karmazinuk and Helik (2025) show that the integration of emotionally intelligent design features into adaptive learning environments (e.g., reflective prompts, emotionally responsive simulations, feedback loops) can greatly enrich cognitive as well as interpersonal skill acquisition (Karmazinuk & Helik, 2025). Their study offers empirical evidence that AI can serve as a scaffold for concept learning, while concomitantly promoting empathic understanding, conflict resolution and teamwork skills—competencies that are crucial in high-stakes defence settings. This innovation may be extended to Defence SMEs in the form of emotionally intelligent training systems, which are able to adjust according to a learner's VARK profile and, furthermore, adapt in accordance with ebbs and flows in learners' emotional levels and observable behaviours. For the first time, this would bridge a gap between skills development in the field of technical competence and emotional robustness, the combination of which may ultimately result in maintaining mission readiness and team integrity in military/defence situations.

Research Publications

Part A: Journal Publications

Title of Research Article	Status	Journal Name	Indexing
A Systematic Literature Review on E-Learning at Small and Medium Enterprises (SMEs): Benefits, Challenges and Trends	Published	Empirical Economics Letters, 24 (Special Issue 4): (March 2025) ISSN: 1681-8997	ABDC Listed
Personalised Learning for Indian Defence SMEs: A Study on Learner Preferences and VARK Learning Styles	Published	Journal of Informatics Education and Research ISSN: 1526-4726 Vol 5 Issue 2(2025)	ABDC Listed
Integrating Large Language Models and Personalised Learning in Medical Education: Potential, Challenges, and the Path Ahead – A Systematic Review	Published	Journal of Informatics Education and Research ISSN: 1526-4726 Vol 5 Issue 2 (2025)	ABDC Listed
Study of Training Effectiveness of Personalised Learning in Upskilling Defence SMEs	Accepted for Publication	The IUP Journal of Accounting Research &Audit Practices ISSN: 2583-5211	ABDC Listed

Part B: Conference Details

Title of Research Article	Status	Title of Conference	Certificate of Presentation
Personalised Learning for Indian Defence SMEs: A Study on Learner Preferences and VARK Learning Styles	Presented	International Conference on "Beyond Border Strategies: Challenges & Opportunities" at Mumbai on 21 & 22 March, 25	Yes
Study of Training Effectiveness of Personalised Learning in Upskilling Defence SMEs	Presented	The International Conference on Business and Finance 2025 (ICBF), April 04-05, 25 at Hyderabad	Yes
Analysis of Emerging Technologies for Personalised Learning	Presented	International Research Conference 2022-Reinventing Business Model Through Disruptive Innovation on 09 April 2022	Yes
Analysis of Artificial Intelligence Based Personalised Adaptive Learning (PAL) In Education 4.0: An Exploratory Study	Presented	International Research Conference 2020-Business Architecture in the era of Industry 4.0, 29 Feb 2020	Yes

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